COORDINATED PARTICIPATION OF WIND FARM AND COMPRESSED AIR ENERGY STORAGE SYSTEM IN A DEREGULATED MARKET ENVIRONMENT USING DISTRIBUTIONALLY ROBUST OPTIMIZATION

BY

MOHSEN HASSAN ALDAADI

A Thesis Presented to the

DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the

Requirements for the Degree of

MASTER OF SCIENCE

In

ELECTRICAL ENGINEERING

December 2018

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by **MOHSEN HASSAN ALDAADI** under the direction of his thesis adviser and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN ELECTRICAL ENGINEERING**.

Thesis Committee

Dr. Fahad S. Al-Ismail (Adviser)

Dr. Ali Alawami (Member)

Dr. Mahmoud Kassas (Member)

Dr. Ali A. Al-Shaikhi

Department Chairman

Dr. Salam A. Zummo

Dean of Graduate Studies

20/12/2018

Date

عمادة الدراسات العليا

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To those who care about me and whom I equally care about

ACKNOWLEDGMENTS

My first gratitude and thanks go to Allah, the Almighty, for giving me determination and opportunity to do my master research. Many thanks to the King Fahd University of Petroleum and Minerals management for giving me the chance to achieve my Master's degree. My sincere and deep gratitude to my adviser, Dr, Fahad Alismail, for his support, guidance, and dedication. Also, I would like to thank the committee members, Dr, Ali Alawami and Dr, Mahmoud Kassas for their helpful advice and suggestions. Besides, my thanks go to the Department Chairman, Dr. Ali Al-Shaikhi and the whole faculty of the Electrical engineering department for creating a conducive learning environment. To my wife, I appreciate your love, constant support, and keeping me sane over the past few months. Above all I would like to thank my parents for their many sacrifices over the years without which I would not be the person I am today. Also, I would not forget to remember my friends and colleagues for their encouragement and support

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LIST OF ABBREVIATIONS

ESS	Energy Storage System
CAES	Compressed Air Energy Storage
DRO	Distributionally Robust Optimization
GWEC	Global wind Energy Council
SMD	Standard Market Design
ISO	Independent System Operator
RO	Robust Optimization
WPP	Wind Power Producers
PSP	Pumped Storage Plant
NN	Neural Network
PDF	Probability Density Function
CVaR	Conditional Value at Risk
PSO	Particle Swarm Optimization
BC	Bilateral Contract
Poolco	Pooled based Company
NYISO	New York Independent System Operator
AGC	Automatic Generation Control

DAM	Day Ahead Market
RTM	Real Time Market
WECS	Wind Energy Conversion System
WT	Wind Turbine
WTS	Wind Turbine System
ASM	Ancillary Services Market

Variables

P_t^w	wind power bid directly to energy market [MW]
P_t^{dis}	Discharge power of CAES [MW]
P_t^{ch}	Charge power of CAES [MW]
$P_t^{sr,d}$	discharge Spinning reserve power at time t [MW]
$P_t^{nr,d}$	discharge non-Spinning reserve power at time t [MW]
E_t	Energy level of storage device [MWh]

Parameters

γ_t^{da}	Day-ahead energy price for hour t
γ_t^{sr}	Day-ahead spinning reserve price for hour t
γ_t^{nr}	Day-ahead non-spinning reserve price for hour t
γ_t^{rt}	Real-time energy market Price at time t
$\hat{P}_t^g$	Power production of wind farm
α_{call}^{sr}	Status of calling of spinning reserve
α_{call}^{nr}	Status of calling of non-spinning reserve
P_{max}^c	Maximum charging power of CAES[MWh]
P_{max}^{exp}	Maximum discharging power of CAES[MWh]

E_{min} minimum level of CAES energy capacity [MWh]

E_{max} maximum level of CAES energy capacity [MWh]

η_d discharge efficiency of CAES

η_c charge efficiency of CAES

P_w^r ramping constraint of wind farm

E_t^{st} initial energy of CAES [Mwh]

VOM^{exp} Variable operation and maintenance cost of CAES in discharging mode

VOM^c Variable operation and maintenance cost of CAES in charging mode

HR^{dis} Heat rate of CAES in discharge mode

Π_t^{ng} Natural gas price at time t

QSC Quick start capacity of the CAES

THESIS ABSTRACT

NAME:	Mohsen Hassan Aldaadi
TITLE OF STUDY:	Coordinated Participation of Wind Farm and Compressed Air Energy Storage System in a Deregulated Market Environment Using Distributionally Robust Optimization
MAJOR FIELD:	Electrical Engineering
DATE OF DEGREE:	December 2018

Recently, the penetration of renewable resources, particularly wind power, has dramatically increased around the world. This increase in wind power penetration poses significant risks, power system reliability and stability, mainly due to the uncertain behavior of wind power output. Furthermore, due to the intermittent nature of wind power generation, participating in the energy and ancillary services market is considered a challenge. The application of energy storage systems (ESSs) is regarded a practical solution to overcome these challenges. This thesis investigates the combination of wind farms and a compressed air energy storage system (CAES) from the viewpoint of a private owner for participation in deregulated electricity markets. Because the CAES can compensate for the uncertainty

in wind farm output, the wind farm will be capable of taking part in the electricity market. In particular, distributionally robust optimization (DRO) will be used to model and analyze the simultaneous participation of a combined wind farm and CAES in day-ahead energy and ancillary services markets. Under various uncertain parameters, including market prices, wind power, energy deployment in reserve, and AGC signal, the optimization of bidding/offering scheduling is considered. These uncertainties are addressed using an ambiguity set of probability distributions, where the expected worst-case scenario is determined. This method combines the advantages of stochastic and robust optimization. This method excludes the assumption of knowing the exact distribution of an uncertain parameter for stochastic optimization. In contrast to robust optimization, the method consolidates certain statistical data to reduce the conservative results.

ملخص الرسالة

الاسم الكامل: محسن حسن منسي الدعدي

عنوان الرسالة: الإشراك المنسق لمصادر الطاقة المتجددة وأنظمة تخزين الطاقة بإستخدام الهواء المضغوط في عملية التشغيل وتقديم الخدمات المساندة في اسوق الكهرباء المخصصة بإستخدام DRO

التخصص: الهندسة الكهربائية

تاريخ الدرجة العلمية: ديسمبر ٢٠١٨

تزايدت في الآونة الأخيرة انتشار إنتاج الطاقة الكهربائية من خلال استغلال الموارد المتجددة، ولا سيما طاقة الرياح في جميع أنحاء العالم .هذه الزيادة في استخدام طاقة الرياح تشكل مخاطرة كبيرة في ضمان موثوقية نظم الطاقة واستقرارها، ويرجع ذلك أساسا إلى التباين المستمر في مستويات قوة الرياح وعدم التيقن من مطابقتها للتوقعات لإتمام عملية التشغيل وتغطية الأحمال بالشكل المطلوب .لذلك، تضل عملية إشراك طاقة الرياح في سوق الطاقة والخدمات المساندة تحدياً كبيراً من ناحية ضمان الموثوقية ينبغي معالجته.

تعتبر أنظمة تخزين الطاقة حلاً فعالاً يساعد في التغلب على هذه التحديات، لذلك تساهم هذه الأطروحة في التحقق من جدوى الجمع و الموائمة بين محطات إنتاج الكهرباء بالرياح ونظام تخزين الطاقة عن طريق الهواء المضغوط من خلال مشاركة القطاع الخاص في سوق الكهرباء.

تقوم أنظمة تخزين الطاقة في تعويض التباين في انتاج الكهرباء الناتج عن محطات طاقة الرياح وتخزين الطاقة الفائضة مما يعطي مرونة كبيرة في عملية التشغيل الاقتصادي لها .لتحقيق هذا الهدف بالشكل المطلوب يجب تصميم و بناء النظام ضمن نموذج يتطرق لتمثيل التباين في انتاج طاقة الرياح و التذبذب في أسعار السوق من ما يعطي نتائج مرتبطة بالبيانات التحليلية للتوقعات طاقة الرياح و (DRO)خلال إيجاد الحل الأمثل بواسطة الأسعار في سوق اليوم المسبق و سوق الخدمات المساندة . حيث يقوم النظام المطور في هذه الأطروحة في الاستفادة المثلى من جدولة العطاءات والعروض في ظل ظروف مختلفة من التباين وعدم التيقن في أسعار السوق وطاقة الرياح والطلب على الطاقة الاحتياطية لكل ساعة.

CHAPTER 1

INTRODUCTION

1.1 Motivation and Overview

Climate change and global warming are major issues affecting nations around the world due to overdependence on conventional generators. Increasing the penetration of renewable energy resources in their different forms is considered an alternative to mitigate the effects of climate change and global warming. In advanced nations such as China, the USA, Denmark, Germany, Spain and Australia, renewable energy sources are being combined with conventional sources of energy production. The fastest developing renewable energy resource is wind energy, with an annual growth rate of 14%. According to the Global Wind Energy Council (GWEC), in 2017, the wind penetration level reached 40% in Denmark and over 20% in Portugal, Uruguay, Ireland, Spain and Cyprus [1]. However, due to the unpredictable nature of wind velocity, wind farm power output is considered uncertain and has a significant effect on the reliability, stability, and quality of power grid.

Wind uncertainty poses a significant challenge for wind farm owners in participating in a deregulated market. Under a standard market design (SMD), energy offers from generations owners and price bids from retailers are submitted many hours in advance to an independent system operator (ISO), which in turn decides the dispatching scheduling by solving an optimization problem. Because wind energy is considered a nondispatchable resource, scheduling offers even with accurate forecasts is considered a challenge [2, 3].

With the need for large-scale penetration of renewable resources, energy storage systems (ESSs) would be a preferable technology to improve the performance of wind farm power output when synchronized with electric power grids. This preference is due to the ability of ESSs to absorb and deliver power to the grid with a fast response, which can be exploited to compensate for the uncertainty of renewable energy. The value of ESSs for renewable resources has been proven based on their contribution to different areas of electric power industry. ESSs can be utilized with renewable resources in different applications, such as bulk energy, ancillary services, frequency regulation, and peak shaving [4, 5]. As a result, a coordinated combination of wind farms and ESSs will allow their owners to participate in a deregulated marke.

Furthermore, policy regulation and utility regulators are currently trying to engage private investors in renewable resources to install and operate systems as a retailer. Thereby, the primary objective of a wind farm with an embedded ESS from a merchant operator viewpoint would be to obtain profit by exploiting arbitrage in energy market prices. This aim is accomplished usually by optimally storing cheap price electric energy during off-peak times and selling it when electricity price goes up during on-peak periods [6, 7]. As indicated in the literature, many researchers are trying to further maximize the profit of ESSs or a combination of ESSs and wind farms by participating in ancillary services markets. These markets are including regulation spinning/nonspinning reserve and replacement reserve (supplemental reserve).

The issue of uncertainty associated with clearing market prices, deployment of reserve and regulation and renewable power output significantly affects the optimality of optimization problem solving using traditional methods. Stochastic programming is one solution to addressing these uncertainties. In this method, the exact probability distribution is needed, which is not always available. Furthermore, given the large size of scenarios, this method can be computationally demanding. Some researchers have proposed using robust optimization (RO) to address these uncertainties. In this approach, it is challenging to incorporate distribution information into the optimization; furthermore, the worst-case realization is sometimes too pessimistic for modeling system uncertainties, resulting in over conservative solutions. Herein, we apply distributionally robust optimization (DRO) to formulate the problem of participating in the deregulated market. This method excludes the assumption in stochastic optimization of knowing the exact probability distribution behavior of an uncertain parameter and by incorporating statistical data the conservative results of robust optimization will be reduced.

1.2 Literature Survey

Because the proposed work will involve the scheduling dispatching of a combination of a wind farm and CAES in the deregulated electricity market, the literature will be examined to investigate the participating owners of wind farms alone, ESSs and distributed energy storage systems and a combination of both in energy and ancillary services markets. Furthermore, a survey will be conducted concerning the CAES and DRO approach that will be used in this research. Because the participation of wind power producers in the deregulated market is considered a challenge, only a few studies have tried to schedule their operation. In [8], a bidding strategy modeled to minimize the imbalanced costs of wind power producers (WPPs) was presented. Stochastic programming was used to formulate the optimization problem based on the Nordic electricity market. The authors of [9] used a risk-based approach to develop an optimal self-scheduling strategy that guarantees to obtain a lower limit of profit from the market considering uncertainty associated with market prices and wind power output. Information gap decision theory was used to model the ambiguity. In this area, stochastic programming incorporating risk aversion-based CVaR methodology was employed to address the uncertainty associated with wind and energy market prices and limit the expected profit [10]. Furthermore, in [11], two-stage stochastic programming was used to optimally schedule the bidding of WPPs by considering different scenarios for addressing the uncertainty. These scenarios were generated using a combination of different techniques.

In the area of ESSs and distributed energy resources, researchers are investigating two directions, either utilizing the operation of ESSs for system-wide benefits (from a systems point of view) or adopting the investor's point of view when profitability is a fundamental concern. In the first direction, large-scale ESSs and distributed energy resources are used to increase the penetration of renewable energy systems by improving their output [12–15], voltage and frequency regulation or enhance the quality of power and reliability of a system [16–20]. In the second direction, the operation of ESSs has been leveraged to seek profit maximization from the investor perspective by participating in the energy market as well as ancillary services that could cope with the high investment and attract merchants to participate in deregulated markets [21–23, 25, 26, 60]. Based on a perfect energy price forecast for one year, the maximum revenue of pump hydro energy storage was highlighted in [21]. EnergyPlan and MATLAB programs were used to simulate a number of different electricity spot markets as evidence to show that with actual day-ahead market prices, high profit could be obtained. The optimal bidding strategy for ESSs participating in the day-ahead energy and spinning reserve market, considering uncertainty in market prices as a result of the integration of renewable energy resources, was studied in [22]. Stochastic programming is used to design a bidding strategy which results in increasing of the profit since the fluctuation of market prices increased significantly with uncertain behaver add by RERs. Further, in [23], stochastic programming approach is used to model the bidding strategy of ESS in not just energy market but even the ancillary services market involves spinning reserve and regulation. The profit from regulation market increased by utilizing a battery's fast regulation services under a performance-based regulation mechanism. Also, the relationship between the life and cycling of the battery is considered. Another paper [60] include the uncertainty of market prices and further the uncertainty associated with the deployment of energy form ESS in reserve and regulation market. The problem formulated using robust optimization and the joint non-sequential mainly the New York market is evaluated in this study.Because all papers mentioned above assumed ESSs as a price taker, which means that their participation in the market will not introduce any effect, the large-scale ESS price maker assumption was considered in [25]. A bidding scheduling for an electric vehicle aggregator participating in a day-ahead market was studied in [26]. The proposed model can decrease the operating cost and simultaneously address the uncertainties of market prices.

In determining the optimal dispatch of a combination of a wind farm and an ESS on a large scale or for distributed energy resources in a deregulated market, different dispatch strategies based on optimization methods have been reported. In [27], the development of a strategy for combining a wind farm and an ESS to bid and mitigate wind power deviation from the day-ahead market was illustrated. In particular, a mixed integer nonlinear optimization was formulated to solve the bidding problem. The author of [28] used rolling stochastic optimization to model a bidding strategy based on the Spanish market for a wind farm embedded with a pumped storage plant (PSP) to participate not only in the day-ahead and in real-time markets but also in the intraday market to maximize the overall profit. Furthermore, in [29], a two-stage stochastic optimization based on a bidding strategy was presented considering the variability of a wind farm and market prices. In this paper, the coordinated and uncoordinated operation of a wind farm and PSP were compared. In [30], a neural network (NN)-based technique was used to construct the probability density function (PDF) of wind power production. Then, stochastic programming was used to optimize the bidding strategy for a combined wind farm and ESS to participate in energy and ancillary markets, but the uncertainty associated with prices was ignored. a bidding strategy using robust optimization was applied in [31, 32] to find the optimal self-scheduling of a wind farm embedded with an ESS to maximize profit by taking advantage of arbitrage in energy market prices. Robust optimization considers uncertainty by using an interval area around the predicted parameter and finds the worst-case scenario of ambiguity within the interval gap. In [32], the conditional value at risk (CVaR) was modeled to address the risk associated with the intermittent nature of wind farm power output and market prices. Then, Monto Carlo simulation was used to test the optimal bidding scheme that generated using robust optimization. In [33], a scheduling bidding strategy was proposed for a coordinated exchange between an electric vehicle and a wind farm generator to participate in the day-ahead energy, balancing and regulation markets.

Different large-scale ESSs can dispatch wind energy to maximize the benefits from arbitrage markets, such as pumped hydro storage (PHS), chemical batteries and compressed air energy storage (CAES). Compared with PHS and chemical batteries, a CAES involves lower investment costs and lower construction limits [20, 28]. Furthermore, CAESs have a long life expectancy and high charging and discharging efficiencies [19]. Currently, the focus of research is to fabricate and design a storage reservoir for CAESs to store air with higher pressure and to eliminate the dependence on geological sites [22]. In addition to the planned systems and those under construction, two CAES plants have been installed. The largest is located in Germany and has a capacity of 390 MW, and the other is in the USA and has a capacity of 110 MW [29]. Some studies have focused on estimating the economic value of either a CAES alone or CAESs coupled with wind farms when participating in the deregulated market [34–38]. An economic analysis was conducted in [34] to estimate the revenues of a CAES in French regulated and deregulated electricity markets. A co-optimized dispatch model for evaluating a conventional CAES and adiabatic CAES in the energy and reserve market was presented in [35]. This study was conducted in multiple regions of the USA, and the results showed that with the added revenue from operating reserves, the conventional CAES is able to support its investment cost, while the adiabatic CAES is not economically viable. For the optimum capacity of a CAES calculated for a wind farm, the daily profit from the energy market for an entire year was estimated based on particle swarm optimization (PSO) in [36], and a sensitivity analysis was included. An economic estimation of the value related to transmission by co-locating CAESs and wind farms was studied in [37]. The author mentioned that this co-location would be less attractive than participating in the ancillary services market. An optimal dispatch algorithm using dynamic programming to maximize the expected profit of a CAES coupled with a wind farm in the energy market was constructed in [38]. As previously mentioned, uncertainties associated with different parameters in the optimization problem, such as prices, wind power output, and deployment of ancillary services, are neglected. These uncertainties could have a significant effect on revenue because the error in forecasting could fluctuate depending on market mechanisms and other factors associated with prediction methods [39]. As a result, uncertainty should be included when modeling bidding strategies and operation scheduling of wind power coupled with a CAES.

Several methods are used to address uncertainty in optimization problems. In [11, 12, 25, 30, 40, 60], stochastic programming, whether chance-constrained or scenario-based, was used to address uncertain parameters in a bidding strategy. This approach attempts to optimize the expected value by considering the exact probability distribution of uncertainties. However, this approach has two computational obstacles: first, it is difficult to know the exact probability distribution of uncertain parameters, and as a function of the number of scenarios, the size of the optimization function increases drastically. A different approach called robust optimization (RO) was used in [3,32,41,43] to address uncertainty in an optimization problem. This method is a deterministic model based on an optimization structure that guarantees feasibility for any realization of an unpredictable parameter over a support set. In this approach, it is challenging to incorporate distribution information appropriately; furthermore, the worst-case scenario is sometimes too pessimistic for modeling system uncertainties, resulting in over-conservative solutions [27]. Recently, a new approach, distributionally robust Optimization (DRO), overcomes the limitations of the methods mentioned above. This type of optimization addresses the uncertainty associated with certain parameters through an ambiguity set that incorporates partial distribution information such as mean, standard deviation, and variances [44]. DRO can optimize the expected value by effectively leveraging data and avoiding the presumption of knowing the exact probability distribution of a random variable for SP. In addition, incorporating statistical information can prevent the conservativism of solving RO problems. Due to the merits of this approach, DRO has been used recently to address different power system problems, i.e., energy and reserve scheduling [44–46], unit commitment [47], optimal power flow problems [48], and to optimally allocate wind farms in a multi area power system with minimizing the energy not supply [49].

1.3 Statement of Research Problem

The uncertain and variable nature of the wind farm power output is a significant problem when participating in energy and ancillary services market. Energy storage system is considered a practical solution to cope with this problem. Furthermore, intermittent associated with the nature of wind and other uncertainties such as market prices, reserve and regulation deployment have to be included in the optimization problem to reach a comprehensive result. Therefore, it is imperative to use optimization methods that deal with several uncertain parameters. In this thesis, the distributionally robust optimization is utilized.

1.4 Objectives of the Research

The objectives of this research are:

- To model the combination of a wind farm and CAES from an investor perspective when participating in the energy and ancillary services market. The importance of participating in multi-markets lies in allowing the owner to further increase profits from other business opportunities and to help recover the investment cost of the CAES. Then, a DRO-based mathematical model is developed to formulate the problem.

- To represent the uncertainties of the renewable energy resources, market prices, and deployment of reserve and regulation markets used in the system as statistical information that is incorporated into the ambiguity set of the DRO model.

- To compare the performance of the proposed DRO model with the robust optimization model.

- To study the influence of the CAES size-based numerical study. This study should assist in finding the optimal size for maximizing profit.

1.5 Thesis Structure

The thesis consists of five chapters. In the following chapter, a background of the main elements in this work which are deregulated electricity market, ancillary services market, CAES, and distributionally robust optimization are reviewed. Chapter three describes the mathematical model of the wind farm and CAES participating in day-ahead energy and ancillary services market. A tested case is included to evaluate the performance of the introduced formulation. The two-stage DRO used in chapter four to reformulate the problem proposed in chapter three with considering all the uncertain parameters in the model. Additionally, the DRO based bidding strategy is compared with robust optimization based bididdng strategy. The thesis conclusion and future work are presented in chapter five.

CHAPTER 2

BACKGROUND

2.1 Wholesale Electricity Markets

In the twentieth century, countries held monopoly system where consumers of electricity do not have the choice of suppliers. In other words, a single organization takes control of the whole system starting from generating ending to users. Whether these organizations owned by private companies or government agencies, geographical monopolies were the standard. Most countries updated the vertically integrated utilities and remodeled them to add competition in generating, transmitting, and distributing the electricity. Figure (2.1) illustrates a generalized structure of a competitive deregulated electricity market. From figure 1, the remodeling of a vertically integrated organization categorized into system operator (ISO) and market participant, i.e., Genco, Disco, and cust.

- **ISO** Is referred to an independent system operator who is responsible for ensuring reliable and secure transmission of energy from sellers to buyers.

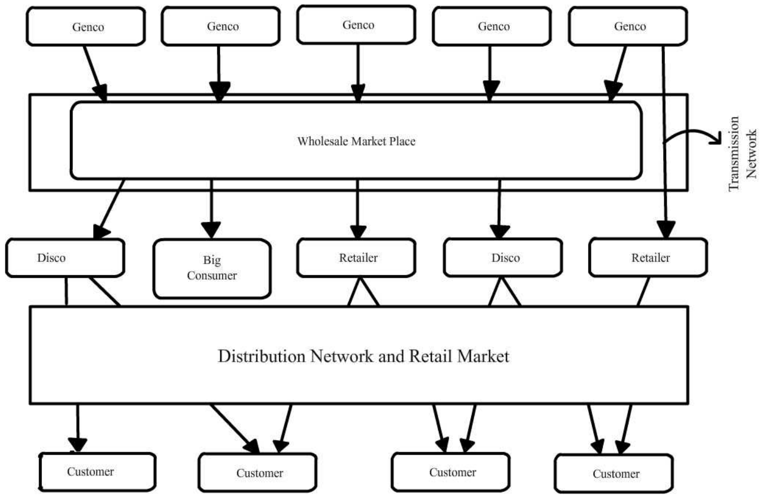

Figure 2.1: competitive wholesale electricity market [50]

Hence, it cannot participate in the electricity market by owning generators, except for reserve capacity for security and reliability cases.

- **Genco** is refered to the generator company who owns one or more generators and this comany will be respensaple of operating and bidding the power into dergulated market enviroment.

- **Disco** is referred to different distribution company owners who responsible for operating a system to deliver electrical power to users and individual businesses. In some deregulated markets, disco is combined with retailer company to over and buy electricity from an energy market and supply it to customers. However, in others, Dico is just responsible for operating their local system, and their revenues will be obtained by billing for supply electricity.

- **Cust** is referred to an entity who receives electricity from suppliers. Customers in the deregulated environment have the option of buying electric power either by bidding in the spot market or directly from Disco.

2.1.1 Electricity Market Models

Different electricity markets have been developed since the liberalized electricity market commencement, which generally can be categorized into bilateral contract (BC) markets, pooled based market (PoolCo) and, hybrid of both [51, 52]. Bilateral contract (BC) is a direct settlement of quantities and prices between buyers "load-serving entities" and seller "wholesale suppliers" without the interference of an ISO [53]. However, In this process, ISO would verify that enough capacity is existing to complete the transaction and maintain the reliability and sustainability of transmission. PoolCo is a centralized market where an independent system operator (ISO) according to the bids and offers from sellers and buyers will clear the market, operate and manages the entire system, and maintains its reliability [52]. Lastly, a hybrid market which gives costumers the option of participating in Poolco based market or bilateral one. As a result, this will generate and create a diversity of opportunities and alternative market prices to indeed provide best individual customer demand satisfaction. Among them, PoolCo is the most commonly used electricity market structure, which contains day-ahead energy and real-time auctions. Participants have the choice of co-operating in either the day-ahead or real-time market. Based on [54], about 94% of total energy is settled in DAM, while the remaining scheduled for RTM.

- **Day-ahead energy market** In most energy markets, a DAM indicates to a forward market at a prespecified zone with locational market prices determined for every hour of the following operating day based on suppliers bids, receivers offers, and other performance schedules included in the market. Day-ahead market bidding involves energy and ancillary services. After the energy market is cleared, suppliers and Load side entities can participate in ancillary service which this transaction could be done in sequentially or simultaneously form as will discussed in the ancillary services section [55].

- **real-time market** Since the real-time values of load and other grid elements will vary from forwarding market settlement, a real-time auction is found to meet the balancing requirements and to ensure the reliability of power systems. Three factors are affecting this settlement the real-time bids, corresponding commitment, and dispatch which all usually operated by an ISO on 5-15 minutes basis. Moreover, generators for supplying imbalances in real-time can be ordered according to their response time, as the regulation which could respond in few seconds following automatic generation control(AGC), the spinning, non-spinning, and the supplemental reserves which could react in minutes of the ISO's requirement instruction [55].

2.1.2 Ancillary Services Market

Ancillary service can be expressed as services required to support the delivery of electricity from generation sectors ending to customers while maintaining a reliable and sustainable energy dispatch. In the United States, these services are procured through day-ahead and Real-time competitive electricity market. In general, participants in the ancillary services market have to submit two parts an energy bid and a capacity bid. Depending on the capacity bids an ISO will clear the market. The second part of the bid is necessary to represent the willingness of participants to be paid if the energy is performed.

Because load in general not precisely predicted, different imbalance fluctuations will occur between load and generation. Frequency regulation service includes the feeding or absorbing small changes of active power to maintain the system frequency. In many nations, frequency regulation or regulation market consider under the secondary frequency control while primary frequency is known as frequency response [56]. Generators and resources whose output altered rapidly and can follow a system operator's automatic generation control (AGC) signal can participate in the regulation market. Reserve services include spinning non-spinning, and supplemental reserve. Spinning reserve indicates to the synchronized generators that designed to response at most in 10 minutes, while non-spinning reserve demonstrates to non-synchronized units that could be brought online in 10 minutes. Units supplying replacement reserve do not need to respond quickly, and in some markets instruction, they have to be available in at most 30 minutes.

There are two mechanisms to clear various ancillary service markets which are sequentially or simultaneously. In the first strategy, a market is cleared in sequential order from the highest quality to the lowest. As a result, the regulation would be cleared first, after that spinning, non-spinning, replacement reserve and so on. However, the participant in one of the services and their bids did not get accepted could rebid in the next one. On the other hand, in the simultaneous method participants in the ancillary services market set their bids once together, and the ISO, in general, would solve an optimization problem to clear the market.

2.2 Compressed Energy Storage System

There are different large-scale ESS that could dispatch wind energy to maximize the benefit from arbitrage markets such as hydro-pumped, chemical and, compressed air energy storages. Chemical batteries are a popular one among them but due to its high investment and recycling cost and its environmental issues which limit its large-scale applications [20]. Another utility-scale energy storage system is hydro-pumped energy storage system which is considered as a mature technology and has more implementation experience comparing to CAES. However, it is restricted on site where reservoirs at differential elevation are available or can be structured, and further, it is environmental damage has effects on its implementation [28].On the other hand, the CAES is characterized by its long life expectancy, low investment and recycle cost, and its high charging and discharging efficiencies [19]. Furthermore, it has fewer construction limits and more cost-effective compared to pumped energy storage.

CAES is a modified version of the conventional gas generator that could even storage electric energy in the form of pressured air. It is composed of a motor,

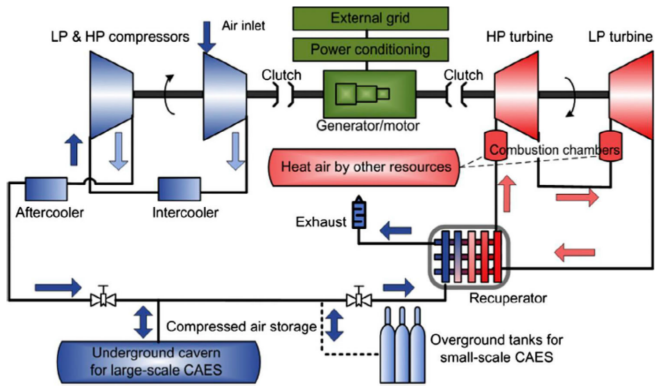

Figure 2.2: Compressed Air Energy Storage System Structure [57]

compressor, reservoir, turbines. As seen in figure 2.2, the motor is used to drive the compressor to compress the air which will be stored inside a reservoir. The intercooler is used to mitigate the temperature of the compressed air. Later when the electrical energy is needed, the pressured air will be preheated in the combustion chamber using natural fuel to drive the turbine. CAES can be structured depending on its application in several sizes and discharge time durations with reasonable response time

Revolution of CAES development started in 1949 when S. Leval innovate the idea of storing electrical energy in the form of compressed air inside an underground reservoir. Currently, the focusing of research is to fabricate and design a storage reservoir for the CAES to store air with higher pressure and to eliminate the dependency on geological site [22]. Besides the planned and under construction CAESs, there are two plants in operation. One in Germany with 290MW capacity and another one in the USA with 110MW capacity [29].

2.3 Distributionally Robust Optimization

Parameter uncertainty considers a significant problem that affects optimization in the mathematical programming community. One method to address this problem is using the stochastic programming approach which widely adopted in planning and scheduling problems in different aspects [31]. This approach is trying to optimize the expected realization by considering the probability distribution of uncertain parameters which is sometimes unavailable. Another approach called Robust Optimization (RO) has been used to address the uncertain parameter in the optimization problem. This approach optimizes the worst-case value which results in a conservative solution [28].

Distributionally Robust Optimization (DRO) overcome the limitations of the stochastic programming and robust optimization. This approach is optimize the expected worst case scenario while addressing the uncertain parameters using an ambiguity set of distribution information such as support sets, mean values, and variances [20].

In stochastic optimization, the minimization expected value of an uncertain function $L(x, \eta)$ is defined as follow:

$$\min_{x} E_p\{l(x, \eta)\} \tag{2.1}$$

where $\eta = [\eta_1 \ldots \eta_n]^T$ is a n-dimensional vector of ambiguous variable and the decision variables expressed by x. Without knowing the distribution of uncertain parameter η, the solution of (2.1) consider in tractable.

Distributionally robust optimization (DRO) involves optimizing the expected worst-case realization of the function $l(x, \eta)$ under all statistical information $\mathcal{P}$ belonging to an ambiguity set $\mathcal{D}$. The DRO problem is thus posed as follows:

$$\min_{x} \sup_{\mathcal{P} \in \mathcal{D}} E_p\{l(x, \eta)\} \tag{2.2}$$

The ambiguity set $\mathcal{D}$ constitutes a family of probability distributions $\mathcal{P}$ modeling the uncertainty set which can be approximated from historical data. Several approaches to modeling the uncertainty set have been proposed by numerous researchers. A common approach to describing the uncertainty set is by including a statistical data with precise mean vector μ and variance matrix σ to arrive at (2.3) [58].

$$\mathcal{D} = \left\{ \mathcal{P}_\eta \in \mathcal{M}_+^M | \begin{array}{c} E_{\mathcal{P}}\{\eta\} = \mu \\ \\ E_{\mathcal{P}}\{\eta - \mu\}\{\eta - \mu\}^T = \sigma \end{array} \right\} \tag{2.3}$$

$\mathcal{M}_+^M$ represents the group of all valid realization on $\mathcal{R}^M$. The mean μ and the variance σ are both determined from historical data. A generalized ambiguity (2.4) set was proposed by [58]

$$\mathcal{D} = \left\{ \mathcal{P}_\eta \in \mathcal{M}_+^M | \begin{array}{c} \mathcal{P}\{\eta \in \Xi\} = 1 \\ \\ (E_{\mathcal{P}}\{\eta\} - \mu)^T \sigma^{-1} (E_{\mathcal{P}}\{\eta\} - \mu) \leq \gamma_1 \\ \\ E_{\mathcal{P}}\{(\eta - \mu)(\eta - \mu)^T\} \leq \gamma_2 \sigma \end{array} \right\} \tag{2.4}$$

In this work, the ambiguity set of the form (2.5) proposed by [47] is considered.

$$\mathcal{D} = \left\{ \mathcal{P}_\eta \in \mathcal{M}_+^M | \begin{array}{l} \mathcal{P}\{\eta \in \Xi\} = 1 \\ \\ E_{\mathcal{P}}\{g_r(\eta)\} \leq \gamma_r \quad r = 1 \ldots I \end{array} \right\} \tag{2.5}$$

The first constraint in (2.5) stipulates that $\mathcal{D}$ contains only valid realization over the support set Ξ. The uncertainties of moment information is characterized by functions $g_i(.)\ \ \forall i \in I$ and also the generalized moment $E_{\mathcal{P}}\{g_i(\eta)\}$ is bounded by known threshold values γ_i in the second constraint. The support set Ξ of uncertainties is defined over lower and upper bounds of the uncertainties as

$$\Xi = \left\{ \eta |\ \eta_n^{min} \leq \eta_n \leq \eta_n^{max}, n = 1, \ldots N \ \right\} \tag{2.6}$$

The moment functions $\{g_i(\eta)\}$, is described by a piecewise linear function as:

$$g_i(\eta) = \max\{f_i^T \eta_i - q_i, 0\},\ \forall i = 1, \ldots I \tag{2.7}$$

Based on (2.6) and (2.7), a lifted support set $\bar{\Xi}$ can be formed as:

$$\bar{\Xi} = \left\{ (\eta, \psi) | \begin{array}{l} \eta \leq \eta^{max} \\ \\ \eta^{min} \leq \eta \\ \\ 0 \leq \psi_r,\ i = r, \ldots I \\ \\ f_r^T \eta - q_r \leq \psi_r, r = 1, \ldots I \end{array} \right\} \tag{2.8}$$

This can be interpreted in compact constraint as:

$$\bar{\Xi} = \left\{ (\eta, \psi) | \ P\eta + R\psi \leq s \ \right\} \tag{2.9}$$

The matrices P, R and s are defined as:

$$P = \begin{bmatrix} I \\ \\ -I \\ \\ 0 \\ \\ F^T \end{bmatrix}, R = \begin{bmatrix} 0 \\ \\ 0 \\ \\ -I \\ \\ -I \end{bmatrix}, s = \begin{bmatrix} \eta^{max} \\ \\ -\eta^{min} \\ \\ 0 \\ \\ q \end{bmatrix} \tag{2.10}$$

.

CHAPTER 3

DETERMINISTIC PROBLEM FORMULATION

3.1 Introduction

In this chapter, an explanation of the physical model for the wind farm and CAES combination is included. After that a deterministic problem formulation with specifying the decision variables and the uncertain parameters is introduced. Finally, the performance of the objective function was evaluated by simulations using a perfect forecast of wind, market prices, reserve deployment, AGC signal. A detailed description of the profits gained from the three cases is also presented.

3.2 Wind Farm and CAES Combination in Deregulated Electricity Market

The non-sequential PoolCo market structure is adapted in this work since it is the most used and in line with PJM, NYISO, CAISO, and ERCOT. The non-sequential markets differ from others by simultaneously co-optimize energy and ancillary services commodities [60]. The combined Wind-CAES will bid in day-ahead energy and ancillary services market. As seen in figure 1, there is one source of energy to feed the CAES which is wind energy. The construction of CAES which contain a high-pressure compressor, reservoir, and expander. The CAES is used to maximize the profit by storing a part of the wind energy as a pressured air in the reservoir using a compressor when market prices are low and then dispatch this energy when energy prices go up using expender.

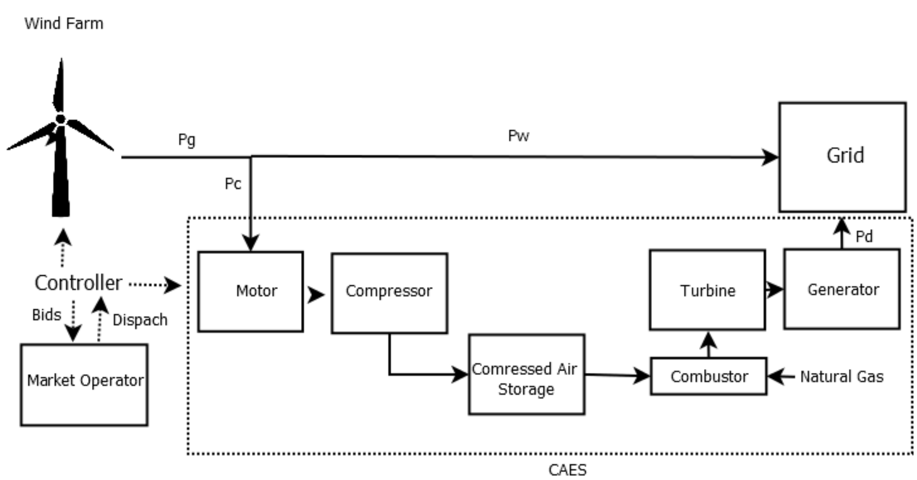

Figure 3.1: Wind Farm and CAES combination structure in deregulated electricity market

Moreover, the CAES will participate in spinning, non-spinning reserve and regulation markets to seek more business opportunities to increase the profit. In contingency reserves market if the CAES is called to deploy spinning or non-spinning reserve capacity, CAES will further receive a payment based real-time energy prices. A similar manner there is another payment in the regulation market when CAES following AGC signal, pay-for-performance schemes, which all modeled in the objective. Similar to [3, 61] we assumed CAES could only be charged using wind energy. Unlike other energy storage system, CAES fed using electricity to power compressors using a motor and natural gas to power the turbine using combustor. As a result, the efficiency of CAES to be quantified, heat flow and energy rate must be involved. Heat rate corresponds to the amount of fuel used per unit of electricity produced using expander [62]. Energy ratio represents the amount of energy used from a wind farm to compress air inside the reservoir (salt cavern) per unit of energy dispatched to the grid [63].

3.3 Problem Formulation

The optimization problem is modeled for seeking the maximum profit could be earned for a system include wind farm and CAES by participating in multimarket. The bidding strategy problem is formulated to maximize the profit by optimally specify the hourly bids for joining the day ahead energy, spinning reserve, non-spinning reserve, and regulation market. Due to the inter-temporal variation of day ahead energy market prices, CAES is applied to exploiting this arbitrage opportunity by storing energy from wind farm when the price is low and sell it when the price is high. The CAES is gain more profit by further bids in the ancillary services market. The wind-CAES operation is assumed as self-scheduling, i.e., the owner is willing to sell or purchase a bid quantity with the marginal prices of the considered market. Also, they are handled in this work as a price-taker which their bids will not influence the market clearing price. The objective function and the constraints expressed as follows:

$$
\begin{aligned}
&\max \sum_{t \in T} \Big[\gamma_t^{e} (P_t^{w} + P_t^{dis}) + \gamma_t^{sr} P_t^{sr,d} + \gamma_t^{nr} P_t^{nr,d} + \gamma_t^{reg} P_t^{reg,d} \\
&+ \gamma^{rt} [P_t^{sr,d} \alpha_{call}^{sr} + P_r^{nr,d} \alpha_{call}^{nr}] + \gamma_t^{reg,m} R_{mil} P_t^{reg,d} \\
&- (P_t^{dis} + P_t^{sr,d} \alpha_{call}^{sr} + P_r^{nr,d} \alpha_{call}^{nr} + 2\beta_t P_t^{reg,d})(HR^{dis} \Pi_t^{Ng} \\
&+ VOM^{exp}) - P_t^{ch} VOM^{c} \qquad (3.1)
\end{aligned}
$$

subject to:

$$\alpha_t^{ch} + \alpha_t^{dis} \leq 1 \tag{3.2}$$

$$0 \leq P_t^w + P_t^{ch} \leq P_t^g \tag{3.3}$$

$$-P_w^r \leq P_t^w - P_{t-1}^w \leq P_w^r \tag{3.4}$$

$$\alpha_t^{ch} P_{min}^c \leq P_t^{ch} \leq \alpha_t^{ch} P_{max}^c \tag{3.5}$$

$$P_t^{dis} + P_t^{sr,d} + P_t^{reg,d} \leq \alpha_t^{dis} P_{max}^d \tag{3.6}$$

$$\alpha_t^{dis} P_{min}^d \leq P_t^{dis} \tag{3.7}$$

$$0 \leq P_t^{reg,d} \leq P_t^{dis} \tag{3.8}$$

$$0 \leq P^{nr} \leq QSC(1 - (\alpha_t^{ch} + \alpha_t^{dis})) \tag{3.9}$$

$$E_{min} \leq E_t - \frac{P_t^{dis} + P_t^{reg,d} + P_t^{sr,d} + P_t^{nr,d}}{\eta_d} \tag{3.10}$$

$$E_t + P_t^{ch} \eta_c \leq E_{max} \tag{3.11}$$

$$E_t^{st} = E_t^{end} \tag{3.12}$$

$$E_{t+1}^s = E_t^s + P_t^{ch} \eta_c - \frac{(P_t^{dis} + \alpha_{call}^{sr} P_t^{sr,d} + \alpha_{call}^{nr} P_t^{nr,d})}{\eta_d} \tag{3.13}$$

The first part of the objective function (3.1) includes energy arbitrage revenue for the wind farm and CAES from day-ahead energy market. The second and third part is the revenue of CAES capacity participating in spinning and non-spinning reserve. The fourth part is the payment of participating in the regulation market as a capacity. The fifth and sixth part as we aforementioned in the market structure is an extra payment based on real-time prices for the called capacity in reserve market. The pay for performance structure is modeled in the ninth part. The last two parts are for the operation cost which expressed as operation cost during discharging mode and operation cost during charging mode. The first one includes the price of natural gas and VOM cost of CAES while in the second mode it only involves VOM cost. Since the CAES system can only operate on charge or discharge mode at a specified time, constraint (3.2) is provided to limit the occurrence of the two modes. Constraint (3.3) implies that the summation of the wind farm bid and the charged power has to be less than or equal the wind farm generation and greater than or equal zero at every hour. The wind power output between two consecutive time intervals is limited by the ramping up/down constraints (3.4). The charging power by the compressor is limited to its maximum and minimum limit which expressed in constraint (3.5). Similarly, (3.6) and (3.7) constraint the injected power from the CAES to its power capacity limit. The bidding in the regulation market should be less than or equal to the bid in the energy market (3.8). If the CAES in idle mode neither charging nor discharging, it can bid in non-spinning reserve limited by the QSC (3.9). The energy constraint of CAES is stated in (3.10) and (3.11).The SOC in end of the day will be equal to the SOC in beginning of the day (3.12). Constraint (3.13) describes the dynamic behavior of the CAES.

3.4 Numerical Results

The optimization problem is formulated for operation scheduling of wind farm and CAES with the capacity of 320MW and 720MWh respectively. The optimal bidding is found based on the deterministic optimization approach with assuming perfect forecasts of wind power output, market prices, reserve deployment, and the AGC signal. Market and operational data are taken from NYISO websit [64], while the wind power data for a hypothetical wind power plant located in New York is used and are available in NREL website [65]. Market prices for day-ahead energy, spot, spinning reserve, non-spinning reserve, regulation capacity,and regulation movement market prices are shown in figure (3.2).

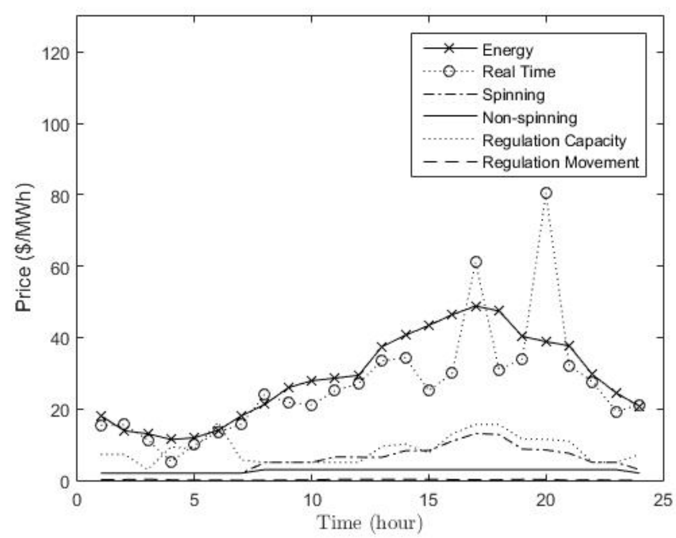

Figure 3.2: Market prices

The characteristic of the CAES in table (3.1) is obtained from [43, 66]. The optimization problem is determined using YALMIP toolbox in MATLAB to find the optimal scheduling of the Wind-CAES system when participating in energy market alone, energy and reserve market, energy, reserve, and regulation market.

Table 3.1: CAES data

Parameter	Value	Unit
$P^{exp}_{max}, P^{exp}_{min}$	120,30	MW
P^{c}_{max}, P^{c}_{min}	90,10	MW
E_{max}	720	MWH
HR_d	0.4185	GJ/MWh
VOM^{exp}, VOM^{c}	0.87	\$/MWh
Round Trip efficiency	75%	Constant
Π^{Ng}_t	3.5	\$/GJ.A

3.4.1 The optimal bidding scheduling in energy market alone

Figure (3.3) and (3.4) present the coordination bidding scheduling of the wind farm and the CAES in the energy market for the given 24 hours horizon. In figure (3.2), the forecast LMP of the first eight hours are low; hence, the bidding decision is made in these hours to dispatch part of the wind power output in Figure (3.3) to charge the CAES as seen in (3.4). Later in hours 14,15,16,17, and 18 when the peak prices reached, the CAES used the compressed air in the reservoir to generate electricity to the grid. In hour 23, the CAES is charged again using the wind power output to prepare itself for the next operating day. The state of charge (SOC) dynamic behavior is shown in Figure (3.5). The total profit for the 24 hours operation horizon based the deterministic optimization is \$60975.

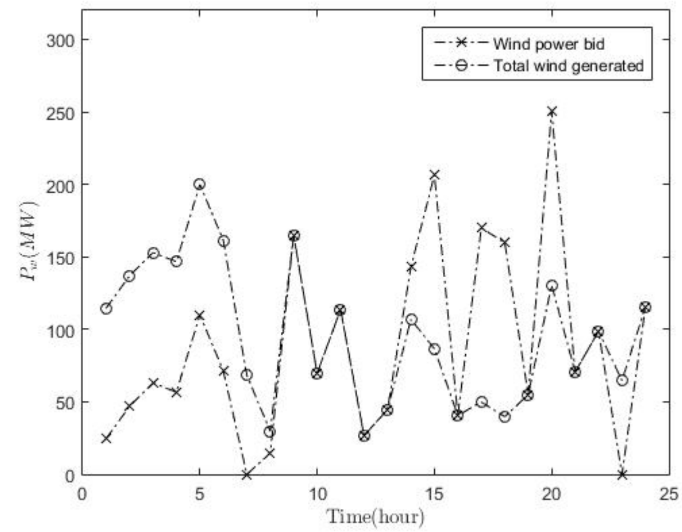

Figure 3.3: Wind farm dispatch in the first considered market

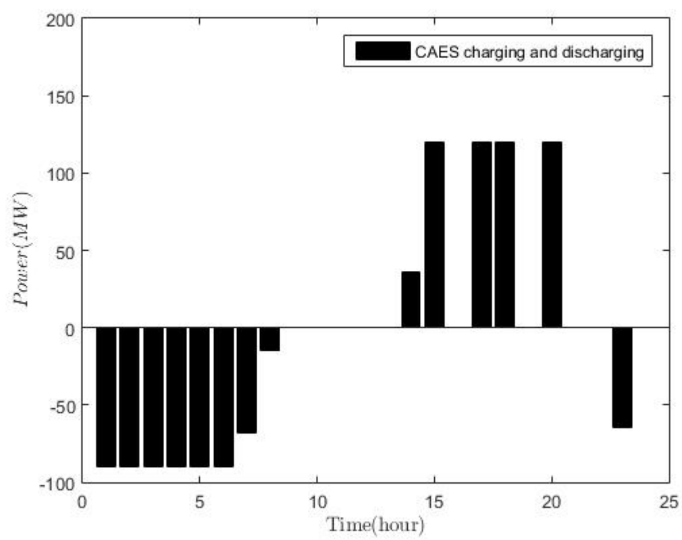

Figure 3.4: Compressing and expanding of the CAES in the first considered market

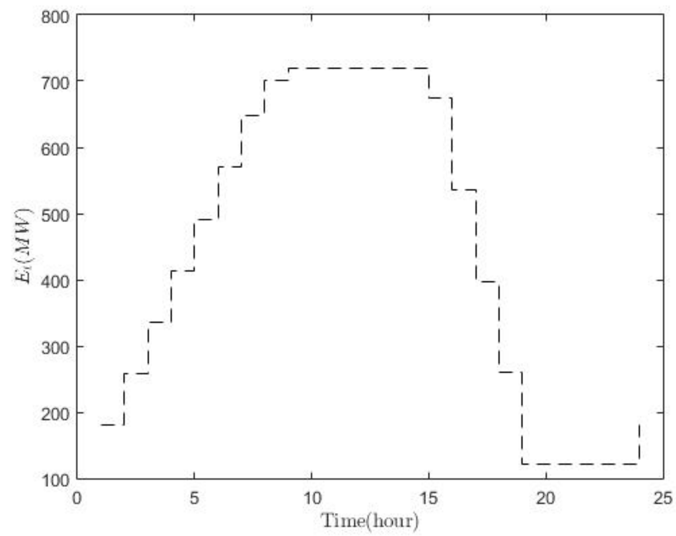

Figure 3.5: Air reservoir level in the first considered market

3.4.2 The optimal bidding scheduling in energy and reserve market

In this part, the optimal bidding scheduling of the wind farm and CAES participating in energy and reserve market are demonstrated in Figure (3.6), (3.7) and (3.8) for the used 24 hours horizon. Based on the input data, the bidding schedule is submitted to charge the CAES at the first seven hours. Later the CAES seeks to maximize the profit by optimize the bidding in energy and spinning reserve market starting from hour 9 to 22. Furthermore, in the Idle mode, the CAES takes advantage by participating in the non-spinning reserve at hour 8, 23 and 24. We can see in Figure (3.8) that the SOC at the end of the day is returned to 25% of the total capacity to adjust itself for the next operating day. The total profit for the 24 hours operation based the deterministic optimization is \$66788.

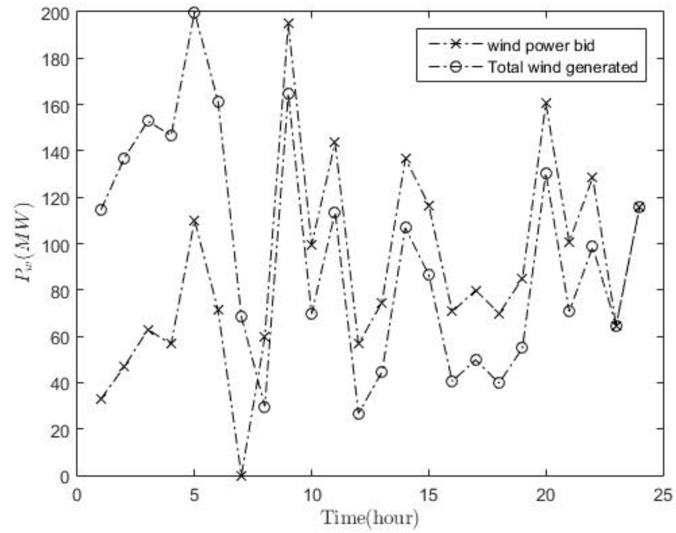

Figure 3.6: Wind farm dispatch in the second considered market

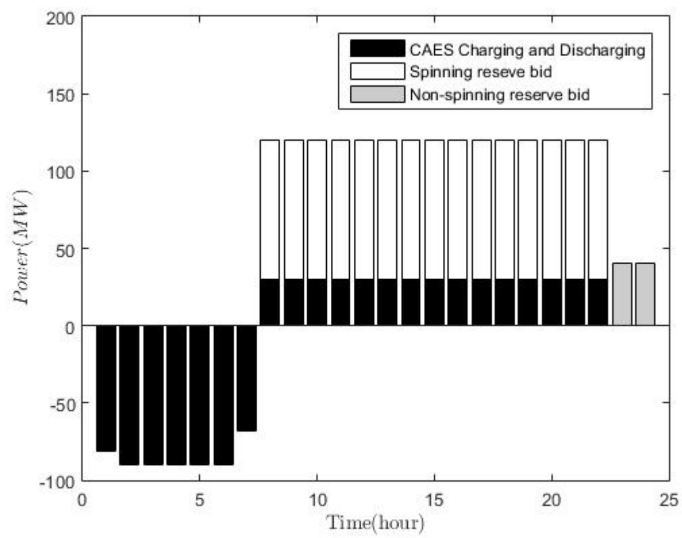

Figure 3.7: Compressing and expanding of the CAES in the second considered market

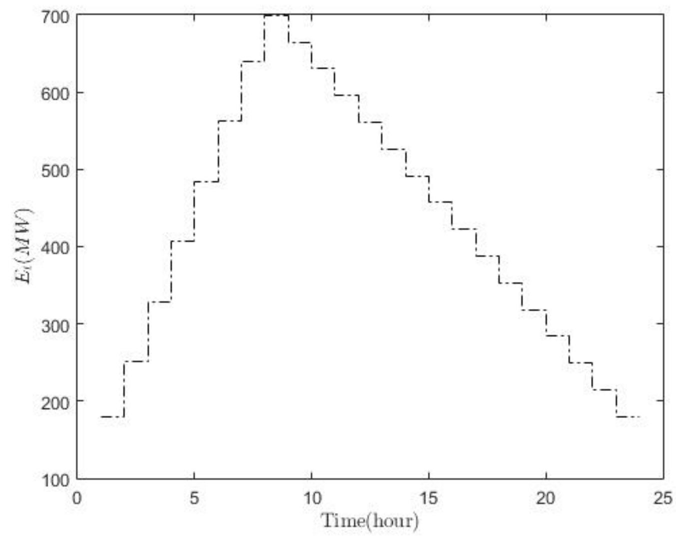

Figure 3.8: Air reservoir level in the second considered market

3.4.3 The optimal bidding scheduling in energy, reserve, and regulation market

The regulation market model is added to the optimization problem to determine the optimal bidding strategy as seen in figure (3.9), (3.10) and (3.11). In a similar manner to the two preceding subsection, the combination of the wind farm and CAES seeks to maximize the profit in energy, reserve, and regulation markets. We can see in figure (3.10) that part of the wind power output used to charge the CAES in the first seven hours. Then, the wind power dispatched using the CAES to participate in energy, reserve and regulation markets. The air level in the reservoir is presented in figure (3.11) which shows that the CAES cannot bid in reserve or regulation markets unless it has enough capacity. The total profit for the 24 hours horizon based the deterministic optimization is $68912.

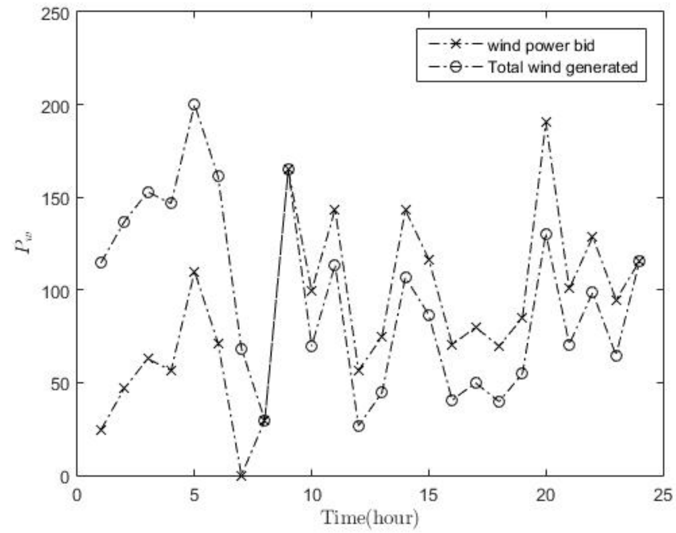

Figure 3.9: Wind farm dispatch in the third considered market

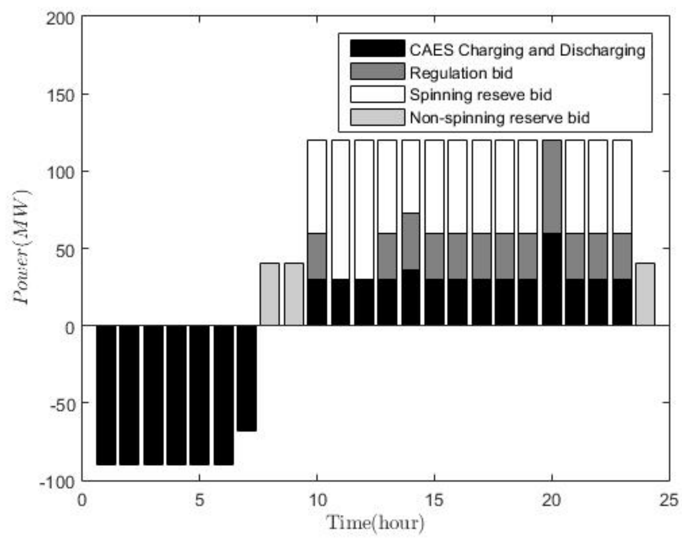

Figure 3.10: Compressing and expanding of the CAES in the third considered market

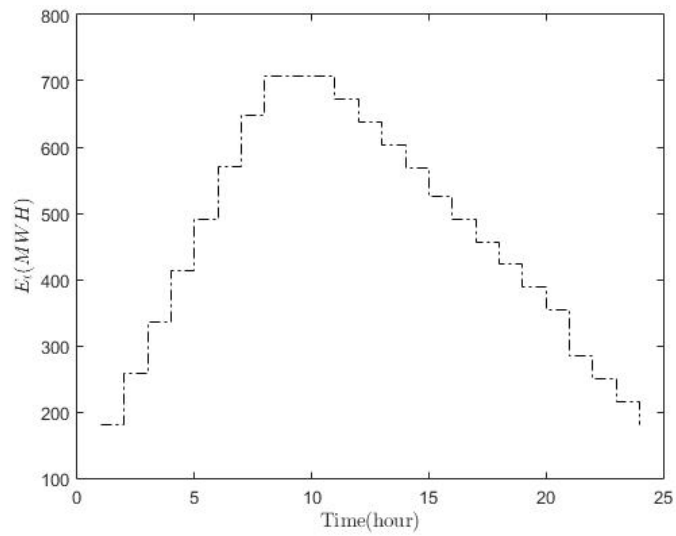

Figure 3.11: Air reservoir level in the third considered market

3.4.4 Comparison between the three considered markets

A profit comparison of the coordination participation of the wind farm and CAES in the energy, energy and reserve, energy, reserve, and regulation markets is presented in figure (3.12). The total profit gained from participating in the energy market is \$60975. In the second bar when the Wind-CAES bids in the energy and reserve market, the profit increased to \$66788 which \$10142 is obtained from spinning and non-spinning reserve market. The third bar is the sum of the profits from energy, reserve, and regulation. Joining the regulation market in the optimization added extra \$6135 to the total profit \$64214.

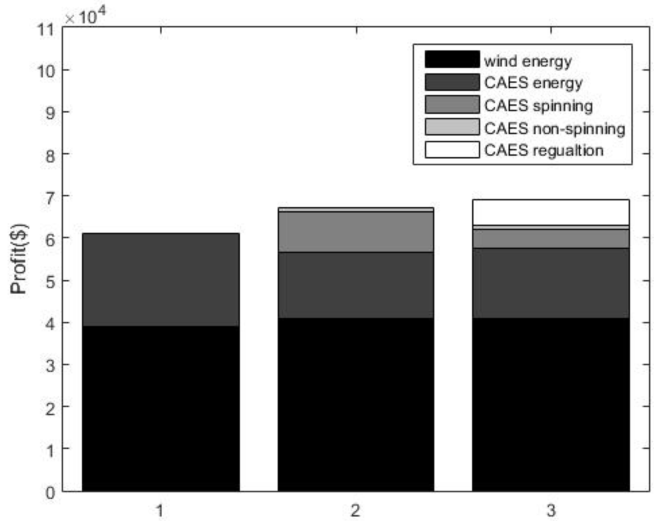

Figure 3.12: Gained profit from participation in three considered markets

CHAPTER 4

DAY-AHEAD ENERGY AND ANCILLARY SERVICES MARKET DESIGN USING DRO

4.1 Introduction

In this chapter, the decision variables and uncertain parameters are defined. After that, a reformulation of the objective function in the preceding chapter using a two-stage distributionally Robust Optimization is included. Furthermore, the defined system uncertainties are managed using ambiguity sets. Simulation results are used based on a case study to compare the participating in the day-ahead energy market alone, with reserve market, and with reserve and regulation markets.

Also, a comparison between DRO and robust optimization are demonstrated to show how including specific statistical data will reduce the conservatism of the result.

4.2 Problem Reformulation

4.2.1 Uncertainty and Compact Matrix Formulation

Generally, In the day-ahead electricity energy market and ancillary services, participants are required to submit their bids several hours before the start of operating day. As seen in figure 4.1, the DAM timeline of New York market, NYISO requires from participants to bid and offer for the next day at 5 AM of the current day. Since the gap between the bidding time and the operation day is 19 to 43 hours, this will result in a highly uncertain wind forecast. Furthermore, bidding will depend on other uncertain forecasts such as market prices, spinning and non-spinning reserve deployments, and AGC signals.

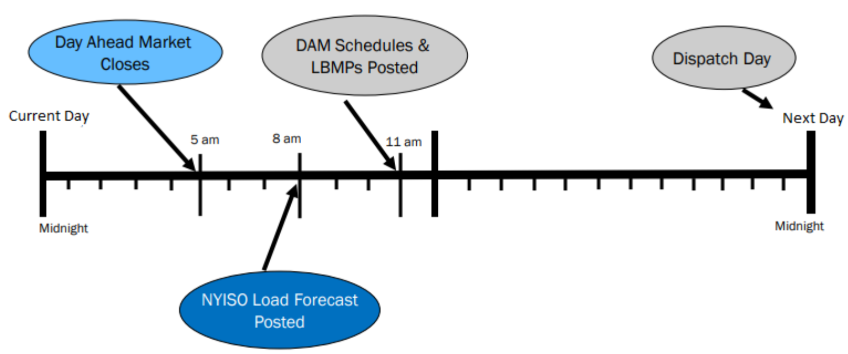

Figure 4.1: Day-ahead market time line [68]

As a result, a two-stage distributionally robust optimization is used in this work to schedule the bids decisions in the first stage while in the second stage the decisions made related to the operation of the CAES and wind farm after the uncertainties are uncovered. Hence, the extracted solution of the two-stage DRO optimization is a single one-stage policy with correction actions made in response to the system uncertainties [69]. To reformulate the problem in (3.1), we first have to define the uncertain parameters and the decision variables then we can write the compact matrix formulation. The purpose of writing the compact matrix formulation is to simplify the analysis of the reformulation. Throughout the reformulation, the matrices and vectors are expressed by bold lowercase letters while entries of matrices and vector are represented by regular letters with subscripts denoting the indices. The decision variables in the objective function (3.1) are $\{P_t^w, P_t^{dis}, P_t^{ch}, P_t^{sr,d}, P_t^{nr,d}, P_t^{reg,d}\}$ while the uncertain parameters are $\{P^g, \gamma^e, \gamma^{sr}, \gamma^{nr}, \gamma^{reg}, \gamma^{reg,m}, \gamma^{rt}, \alpha_{call}^{sr}, \alpha_{call}^{nr}, R_{mil}\}$. In the first stage, the decisions variables are represented by $\boldsymbol{x} \in \mathbb{R}^{|\mathcal{K}|}$, where $\mathcal{K}$ is the set of all decisions variables. The decision variables in the second stage are expressed by a vector $\boldsymbol{y}$. Hence the objective (3.1) and constraints (3.2)-(3.14) are of the form:

$$\min \sup_{\mathbb{P}\in\mathbb{G}} \mathbb{E}_{\mathbb{P}} \left\{\mathcal{L}(\boldsymbol{x}, \tilde{\boldsymbol{c}})\right\} \tag{4.1}$$

$$\text{s.t. } \boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{b} \tag{4.2}$$

with $\boldsymbol{A} \in \mathbb{R}^{|\mathcal{V}|\times|\mathcal{K}|}$ and $\boldsymbol{b} \in \mathbb{R}^{|\mathcal{V}|}$; where $\mathcal{V}$ is the set of all constraints. The function $L(\boldsymbol{x}, \boldsymbol{c})$ is determined in the second-stage with the effect of uncertain parameters and this function are expressed by

$$\mathcal{L}(\boldsymbol{x},\boldsymbol{c}) = \min \ \boldsymbol{f}^T\boldsymbol{y} \tag{4.3}$$

$$\text{s.t. } \boldsymbol{E}(\boldsymbol{c}) + \boldsymbol{T}\boldsymbol{y} \leq \boldsymbol{q}(\boldsymbol{c}) \tag{4.4}$$

In this expression $\boldsymbol{f} \in \mathbb{R}^{|\mathcal{K}|}$, $\boldsymbol{E}(\boldsymbol{c}) \in \mathbb{R}^{|\mathcal{V}|\times|\mathcal{K}|}$, $\boldsymbol{T} \in \mathbb{R}^{|\mathcal{V}|\times|\mathcal{K}|}$, and $\boldsymbol{q}(\boldsymbol{c}) \in \mathbb{R}^{|\mathcal{V}|}$. constraints of the second stage problem (4.4) are included as inequality constraint which suggested by (3.3) where the right-hand-side matrix $\boldsymbol{E}(\boldsymbol{c})$ and the lift-hand-side vector $\boldsymbol{q}(\boldsymbol{c})$ are influenced by the uncertain parameter $\boldsymbol{c}$. The matrix $\boldsymbol{E}(\boldsymbol{c})$ and vector $\boldsymbol{q}(\boldsymbol{c})$ are expressed as the following linear affine equations

$$\boldsymbol{E}(\boldsymbol{c}) = \boldsymbol{E}^0 + \sum_{m\in\mathcal{M}} \boldsymbol{E}^c_m c_m \tag{4.5}$$

$$\boldsymbol{q}(\boldsymbol{c}) = \boldsymbol{q}^0 + \sum_{m\in\mathcal{M}} \boldsymbol{q}^c_m c_m \tag{4.6}$$

4.2.2 Ambiguity Set

In this section, the uncertain parameters of the objective function (3.1) modeled using an ambiguity set $\mathbb{G}$ that defines a family of distribution [58]. The wind uncertainty can be modeled in the ambiguity set using the expressions (4.7)-(4.10).

$$\mathbb{P}\left\{\tilde{\boldsymbol{P^g}} \in \mathcal{W}\right\} = 1 \tag{4.7}$$

$$\mathbb{E}_{\mathbb{P}}\left\{\tilde{P}_t^g\right\} = \bar{P^g}_t, \forall t \in \mathcal{T} \tag{4.8}$$

$$\mathbb{E}_{\mathbb{P}}\left\{|\tilde{P^g}_t - \bar{P^g}_t|\right\} \leq \phi_t^w, \forall t \in \mathcal{T}, \tag{4.9}$$

$$\mathbb{E}_{\mathbb{P}}\left\{(\tilde{P^g}_t - \bar{P^g}_t)^2\right\} \leq \lambda_t^w, \forall t \in \mathcal{T} \tag{4.10}$$

The first constraint (4.7) ensures that the random generated wind power vector is bounded using a support set $\mathcal{W}$. Similar to the conventional robust optimization, the support set $\mathcal{V}$ is defined with its lower and upper bound by equation(4.11):

$$\mathcal{W} = \left\{\boldsymbol{P^g} |\ P_t^{g-} \leq P_t^g \leq P_t^{g+},\ \forall t \in \mathcal{T}\right\} \tag{4.11}$$

The second constraint (4.8) indicates that the generalized moment of $\mathbb{E}_{\mathbb{P}}\left\{\tilde{P}_t^g\right\}$ is $\bar{P}_t^g$. The inequality constraint (4.9) implies that the mean absolute deviation of $\tilde{P}_t^g$ is not higher than ϕt^w. Lastly, the variance in equation (4.10) is less than or equal to the constant λ_t^w. Obviously, equations (4.7)-(4.10) characterize statistical measures such as expectation, mean absolute deviations, and variances which could be estimated using historical data without the need of an exact probability distribution as the matter with Stochastic programming.

Additional constraints (4.12)-(4.15) are formed in the ambiguity set to characterize the statistical distribution of the market prices. Note that these constraints are a general form for all the uncertain market prices.

$$\mathbb{P}\left\{\tilde{\boldsymbol{\gamma}} \in \mathcal{P}\right\} = 1 \tag{4.12}$$

$$\mathbb{E}_{\mathbb{P}}\left\{\tilde{\gamma}_t\right\} = \bar{\gamma}_t, \forall t \in \mathcal{T} \tag{4.13}$$

$$\mathbb{E}_{\mathbb{P}}\left\{|\tilde{\gamma}_t - \bar{\gamma}_t|\right\} \leq \phi_t^p, \forall t \in \mathcal{T}, \tag{4.14}$$

$$\mathbb{E}_{\mathbb{P}}\left\{(\tilde{\gamma}_t - \bar{\gamma}_t)^2\right\} \leq \lambda_t^p, \forall t \in \mathcal{T} \tag{4.15}$$

The first constraint (4.12) ensures that the random market prices is bounded using a support set $\mathcal{P}$. The Support set $\mathcal{P}$ is defined with its lower and upper bound by equation(4.16).

$$\mathcal{P} = \left\{\boldsymbol{\gamma} | \ \gamma_t^- \leq \gamma_t \leq \gamma_t^+, \ \forall t \in \mathcal{T}\right\} \tag{4.16}$$

The constraints (4.13)-(4.15) represent the expectation, the mean absolute deviation, and the variance which could be determined from historical market prices data.

For reserve deployment similar to [60] the worst case scenario of the historical data is introduced. the last uncertain parameter is excluded in [60] since it's neglected effect on the optimization. In this work, the worst case AGC signals are held. A compact matrix that provides for all the mentioned constraints is expressed as follow.

$$\mathbb{G} = \left\{ \mathbb{P} \in \mathcal{Q}_0\left(\mathbb{R}^{|\mathcal{M}|}\right) : \begin{array}{l} \tilde{\boldsymbol{c}} \in \mathbb{R}^{|\mathcal{M}|} \\ \\ \mathbb{P}\left\{\tilde{\boldsymbol{c}} \in \mathcal{C}\right\} = 1 \\ \\ \mathbb{E}_{\mathbb{P}}\left\{\tilde{c}_m\right\} = \bar{c}_m, \quad \forall m \in \mathcal{M} \\ \\ \mathbb{E}_{\mathbb{P}}\left\{g_n(\tilde{\boldsymbol{c}})\right\} \le \mu_n, \forall n \in \mathcal{N} \end{array} \right\} \tag{4.17}$$

The uncertain parameters (4.7) and (4.12) are combined in the vector $\bar{\boldsymbol{c}}$, where $\mathcal{M}$ is the set of distributions in $\mathbb{R}^{\mathcal{M}}$. The following constraint in (4.17) implies that all distribution of the random vector $\bar{\boldsymbol{c}}$ are within a support set $\mathcal{C}$, which includes all the support sets (4.11) and (4.16). The third constraint in (4.17) is the expected value of randoms variables, which is a generalize form of the constraints (4.8) and (4.13). The last constraint in (4.17) characterize distribution information of uncertainties via $g_n(\tilde{\boldsymbol{c}}$, which is a compact form of the absolute deviation and variance. The expected value of $g_n(\tilde{\boldsymbol{c}})$ expresses the all inequalities constraints (4.9), (4.14), (4.10), (4.15) , where the constants ϕ_t^w, λ_t^w, ϕ_t^p, and λ_t^p are represented by μ_n

Due to The difficulty of estimating the expectation of each function $g_n(\tilde{\boldsymbol{c}})$ under uncertain distributions, The proposed problem is complicated to be solved. To derive a tractable formulation, a set of auxiliary variables are included in the ambiguity set to address the upper bound of the functions. An extended lifted form of $\mathbb{G}$ is expressed as

$$\bar{\mathbb{G}} = \left\{ \mathbb{Q} \in \mathcal{Q}_0\left(\mathbb{R}^{|\mathcal{M}|} \times \mathbb{R}^{|\mathcal{N}|}\right) : \begin{array}{l} (\tilde{\boldsymbol{c}}, \tilde{\boldsymbol{\omega}}) \in \mathbb{R}^{|\mathcal{M}|} \times \mathbb{R}^{|\mathcal{N}|} \\ \mathbb{Q}\left\{(\tilde{\boldsymbol{c}}, \tilde{\boldsymbol{\omega}}) \in \bar{\mathcal{C}}\right\} = 1 \\ \mathbb{E}_{\mathbb{Q}}\left\{\tilde{c}_m\right\} = \bar{c}_m, \forall m \in \mathcal{M} \\ \mathbb{E}_{\mathbb{Q}}\left\{\tilde{\omega}_n\right\} \le \mu_n, \forall n \in \mathcal{N} \end{array} \right\} \tag{4.18}$$

A new joint family of distribution denoted by $\mathbb{Q}$ is introduced for both the random and auxiliary variables. The support set in (4.18) is extended to (4.19).

$$\bar{\mathcal{C}} = \left\{ (\boldsymbol{c}, \boldsymbol{\omega}) \in \mathbb{R}^{|\mathcal{M}|} \times \mathbb{R}^{|\mathcal{N}|} : \begin{array}{ll} \boldsymbol{c} \in \mathcal{C} & \\ g_n(\boldsymbol{c}) \le \omega_n, & \forall n \in \mathcal{N} \\ \omega_n \le \sup\limits_{\boldsymbol{c} \in \mathcal{C}} g_n(\boldsymbol{c}), \forall n \in \mathcal{N} & \end{array} \right\} \tag{4.19}$$

The extended support set implies that the function $g_n(\boldsymbol{c})$ is bounded with the upper limits $\boldsymbol{\omega}_n$. Hence the expected value in (4.17) can't be hold unless the fourth line in (4.18) is satisfied. Since the support set $\mathcal{C}$ is composed of linear expression (4.7) and (4.12) and the function $g_n(\boldsymbol{c})$ is whether quadratic or linear for defining various moment information, these functions are converted into the following second-order cone constraints [49].

$$\bar{\mathcal{C}} = \left\{ (\boldsymbol{c}, \boldsymbol{\omega}) \in \mathbb{R}^{|\mathcal{M}|} \times \mathbb{R}^{|\mathcal{N}|} : \begin{array}{l} \|\boldsymbol{F}_r \boldsymbol{c} + \boldsymbol{H}_r \boldsymbol{c} \le \boldsymbol{h}_r\| \\ \le \boldsymbol{a}_r^T \boldsymbol{c} + \boldsymbol{s}_r^T \boldsymbol{\omega} + e_r,\ r \in \mathcal{R} \end{array} \right\} \tag{4.20}$$

This constraints are used in the next section to dulize the objective into a maximization problem. with $\boldsymbol{F}_r \in \mathbb{R}^{V_r \times |\mathcal{M}|}$, $\boldsymbol{H}_r \in \mathbb{R}^{V_r \times |\mathcal{N}|}$, and $\boldsymbol{h}_r \in \mathbb{R}^{V_r}$, where V_r is the row number for the rth constraint, and the set of all constraints representing the extended support set $\bar{\mathcal{C}}$ are indicated by $\mathcal{R}$. The modified support set $\bar{\mathcal{C}}$ and ambiguity set $\bar{\mathbb{G}}$ are used to reformulate a tractable expectation problem in the next subsection.

4.2.3 Reformulation based on the Generalized Linear Decision Rules Approximation

In a two-stage DRO optimization problem, extracting an explicit expression of the exact optimal solution is generally intractable, since the worst-case expectation of $\mathcal{L}(\boldsymbol{x}, \tilde{\boldsymbol{c}})$ must be determined by solving the recourse policy in (4.3)-(4.4) under all realization of uncertainties within the support set $\bar{\mathbb{G}}$ [70]. This issue is addressed by employing the affine decision rules, which in turn will drive the recourse decision y to be affinely modifying with the uncertainties [71], [72], [73], [74], [75]. In this work, the decision rule function $\bar{y}_k$ is affected by uncertain parameters $\boldsymbol{c}$ and auxiliary variables $\boldsymbol{\omega}$ which are formulated as

$$\bar{y}_k(\boldsymbol{c}, \boldsymbol{\omega}) = y_k^0 + \sum_{m \in \mathcal{M}_k} y_{km}^c c_m + \sum_{n \in \mathcal{N}_k} y_{kn}^{\omega} \omega_n, \ \forall k \in \mathcal{K}_2 \tag{4.21}$$

In this work, the subset $\mathcal{M}_k$ and $\mathcal{N}_k$ consist of random and auxiliary variables that influence the decision $\bar{y}_k$ for the same hour. As a reuslt, a 24 subset is included in this work. A further generalization of the affine decisions rule $\bar{y}_k$ is expressed as

$$\bar{\boldsymbol{y}} = \boldsymbol{y}^0 + \boldsymbol{Y}^c\boldsymbol{c} + \boldsymbol{Y}^\omega\boldsymbol{\omega} \tag{4.22}$$

With $\boldsymbol{y}^0 \in \mathbb{R}^{|K|}$ denotes the constant terms, and $\boldsymbol{Y}^c$, $\boldsymbol{Y}^\omega$ are coefficient matrices where their entries defined by (4.23) and (4.24), are the affine coefficients term that respectively associated with $\boldsymbol{c}$ and $\boldsymbol{\omega}$.

$$Y^c_{km} = \begin{cases} y^c_{km}, & \text{if } m \in \mathcal{M}_k \\ 0, & \text{if } m \in \mathcal{M} \setminus \mathcal{M}_k \end{cases} \qquad \forall k \in \mathcal{K}_2 \tag{4.23}$$

$$Y^\omega_{kn} = \begin{cases} y^\omega_{kn}, & \text{if } n \in \mathcal{N}_k \\ 0, & \text{if } n \in \mathcal{N} \setminus \mathcal{N}_k \end{cases} \qquad \forall k \in \mathcal{K}_2 \tag{4.24}$$

By substituting the affine decision rules approximation for the actual recourse policy $\boldsymbol{y}$ of each uncertainty realization, an approximated formulation of the two-stage DRO problem can be derived as follow.

$$\min \sup_{\mathbb{Q}\in\bar{\mathbb{G}}} \mathbb{E}_{\mathbb{Q}} \left\{ \boldsymbol{f}^T \boldsymbol{y}(\tilde{\boldsymbol{c}}, \tilde{\boldsymbol{\omega}}) \right\} \tag{4.25}$$

$$\text{s.t. } \boldsymbol{Ax} \leq \boldsymbol{b} \tag{4.26}$$

$$\boldsymbol{E}(\boldsymbol{c}) + \boldsymbol{T}\bar{\boldsymbol{y}}(\boldsymbol{c},\boldsymbol{\omega}) \leq \boldsymbol{q}(\boldsymbol{c}), \qquad \forall(\boldsymbol{c},\boldsymbol{\omega}) \in \bar{\mathcal{C}} \tag{4.27}$$

The above conservative formulation yields a lower bound of the expected profit gained from the wind-CAES combination. A semi-infinite representation can be written for the inner supreme as follow.

$$\sup \int_{\bar{\mathcal{C}}} \boldsymbol{f}^T \bar{y}(\boldsymbol{c},\boldsymbol{\omega}) df(\boldsymbol{c},\boldsymbol{\omega}) \tag{4.28}$$

$$\text{s.t. } \int_{\bar{\mathcal{C}}} c_m df(\boldsymbol{c},\boldsymbol{\omega}) = \bar{c}_m, \qquad \forall m \in \mathcal{M} \tag{4.29}$$

$$\int_{\bar{\mathcal{C}}} \omega_n df(\boldsymbol{c},\boldsymbol{\omega}) \leq \mu_n, \qquad \forall n \in \mathcal{N} \tag{4.30}$$

$$\int_{\bar{\mathcal{C}}} f(\boldsymbol{c},\boldsymbol{\omega}) = 1 \tag{4.31}$$

$$f(\boldsymbol{c},\boldsymbol{\omega}) \geq 0, \qquad \forall(\boldsymbol{c},\boldsymbol{\omega}) \in \bar{\mathcal{C}} \tag{4.32}$$

The equations (4.25)-(4.27) are reformulated into the robust optimization problem below which is derived by dualizing the semi-infinite representation

(4.28)-(4.32).

$$\min\ \rho + \bar{\boldsymbol{c}}^T\boldsymbol{\eta} + \boldsymbol{\mu}^T\boldsymbol{\beta} \tag{4.33}$$

$$\text{s.t. } \boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{b} \tag{4.34}$$

$$\rho + \boldsymbol{c}^T\boldsymbol{\eta} + \boldsymbol{\omega}^T\boldsymbol{\beta} \geq \boldsymbol{f}^T\bar{\boldsymbol{y}}(\boldsymbol{c},\boldsymbol{\omega}), \quad \forall(\boldsymbol{c},\boldsymbol{\omega}) \in \bar{\mathcal{C}} \tag{4.35}$$

$$\boldsymbol{E}(\boldsymbol{c})\boldsymbol{x} + \boldsymbol{T}\bar{\boldsymbol{y}}(\boldsymbol{c},\boldsymbol{\omega}) \leq \boldsymbol{q}(\boldsymbol{c}), \qquad \forall(\boldsymbol{c},\boldsymbol{\omega}) \in \bar{\mathcal{C}} \tag{4.36}$$

$$\rho \in \mathbb{R}, \boldsymbol{\eta} \in \mathbb{R}^{|\mathcal{M}|}, \boldsymbol{\beta} \in \mathbb{R}_-^{|\mathcal{N}|} \tag{4.37}$$

constraints (4.29), (4.30), and (4.31) are expressed by the dual variables $\boldsymbol{\eta}$, $\boldsymbol{\beta}$, and ρ respectively. Reaching to a classic robust optimization problem with a tractable polyhedral uncertainty set $\bar{\mathcal{C}}$, which can be represented as the following robust counterpart.

$$\min\ \rho + \bar{\boldsymbol{c}}^T\boldsymbol{\eta} + \boldsymbol{\mu}^T\boldsymbol{\beta} \tag{4.38}$$

$$\text{s.t. } \boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{b} \tag{4.39}$$

$$\rho - \boldsymbol{f}^T\boldsymbol{y}^0 + \sum_{r\in\mathcal{R}} \left(\boldsymbol{h}_r^T\boldsymbol{\pi}_r^0 + e_r\zeta_r^0\right) \geq 0 \tag{4.40}$$

$$\sum_{r\in\mathcal{R}} \left(\boldsymbol{F}_r^T\boldsymbol{\pi}_r^0 - \zeta_r^0\boldsymbol{a}_r\right) = \boldsymbol{\eta} - \boldsymbol{Y}^c\boldsymbol{f} \tag{4.41}$$

$$\sum_{r\in\mathcal{R}} \left(\boldsymbol{H}_r^T\boldsymbol{\pi}_r^0 - \zeta_r^0\boldsymbol{s}_r\right) = \boldsymbol{\beta} - \boldsymbol{Y}^\omega\boldsymbol{f} \tag{4.42}$$

$$\|\boldsymbol{\pi}_r^0\| \leq \zeta_r^0, \qquad \forall r \in \mathcal{R} \tag{4.43}$$

$$\boldsymbol{\pi}_r^0 \in \mathbb{R}^{V_r},\ \zeta_r^0 \in \mathbb{R}_+, \qquad \forall r \in \mathcal{R} \tag{4.44}$$

$$\left(\boldsymbol{E}^0\boldsymbol{x} + \boldsymbol{y}^0\right)_v \leq q_v^0 + \sum_{r\in\mathcal{R}} \left(\boldsymbol{h}_r^T\boldsymbol{\pi}_r^v + e_r\zeta_r^v\right), \qquad \forall v \in \mathcal{V}_2 \tag{4.45}$$

$$\sum_{r\in\mathcal{R}} \left(\boldsymbol{F}_r^T\boldsymbol{\pi}_r^v - \zeta_r^v\boldsymbol{a}_r\right)_m = \left(\boldsymbol{d}^m - \boldsymbol{E}^m\boldsymbol{x}\right)_v - \left(\boldsymbol{T}\boldsymbol{Y}^c\right)_{vm}, \qquad \forall m \in \mathcal{M}, \forall v \in \mathcal{V}_2 \tag{4.46}$$

$$\sum_{r\in\mathcal{R}} \left(\boldsymbol{H}_r^T\boldsymbol{\pi}_r^v - \zeta_r^v\boldsymbol{s}_r\right)_m = -\left(\boldsymbol{T}\boldsymbol{Y}^c\right)_{vm}, \qquad \forall m \in \mathcal{M}, \forall v \in \mathcal{V}_2 \tag{4.47}$$

$$\|\boldsymbol{\pi}_r^0\| \leq \mu_r^0, \qquad \forall r \in \mathcal{R} \tag{4.48}$$

$$\boldsymbol{\pi}_r^v \in \mathbb{R}^{V_r},\ \mu_r^v \in \mathbb{R}_+, \qquad \forall r \in \mathcal{R}, \forall v \in \mathcal{V}_2 \tag{4.49}$$

$$\rho \in \mathbb{R}, \boldsymbol{\eta} \in \mathbb{R}^{|\mathcal{M}|}, \boldsymbol{\beta} \in \mathbb{R}_-^{|\mathcal{N}|} \tag{4.50}$$

The constraints (4.40)-(4.44) is the reformulation of the constraint (4.35) after dualizing the extended ambiguity set $\bar{\mathcal{C}}$. The vectors $\boldsymbol{\pi}_r^0$ and μ_r^0 are denoted for the dual variables. In the same manner, by considering dual variables $\boldsymbol{\pi}_r^m$ and μ_r^m, constraints (4.45)-(4.49) are derived from the mth constraint of (4.36). The robust counterpart of the formulated two-stage operation problem is a convex SOCP problem. The linear optimization programming after applying the affine decision rule might be conservative, but it is resulting in much easier computational burden than the original two-stage optimization problem. Based on a case study the effectiveness of the proposed model are demonstrated in the next section.

4.3 Simulation Results

4.3.1 Data

The capacities of the combination are chosen similar to the deterministic case which 320MW for the wind farm and 720MWh for the CAES. The optimal bidding strategy is determined based on a two-stage DRO approach. Historical market and operational data are taken from NYISO website [64] and the historical wind power data for a hypothetical wind power plant located in New York is used and are available in NREL website [65]. The constants of the ambiguity sets are calculated using the historical data for each hour of the operating day and included to assess the result of DRO. The same characteristic of the CAES in table (3.1) is used in this work which obtained from [43, 66]. The two stage DRO problem is solved using the IBM ILOG CPLEX solver where the PC used has with an Intel Core 7 CPU (2.5 GHz) and 8.0 GB RAM.

4.3.2 The optimal bidding scheduling in energy market alone using DRO

AS shown in figures (4.2), (4.3) and (4.4) the optimal bidding strategy in energy alone market using DRO is determined. based on the worst-case expected total wind generation Pg and other uncertain prices, the decision is made to charge the CAES in the first hours and to dispatch the total wind power generated to the grid as seen in figure (4.2). The CAES operation is demonstrated in figure (4.3) where it is trying to be charged in first hours and later in hours 16,17,18,20, and 24 the energy is dispatched to the grid. Note that in figure (4.4) the air reservoir level reached its maximum at hour 10 to prepare itself to dispatch this energy during on-peak when the prices go up. Furthermore, we notice that the state of charge at the last hour reached 25% of its total capacity to be ready for the next day operation. The total worst-case expected profit for the 24 hours based DRO is $46315.

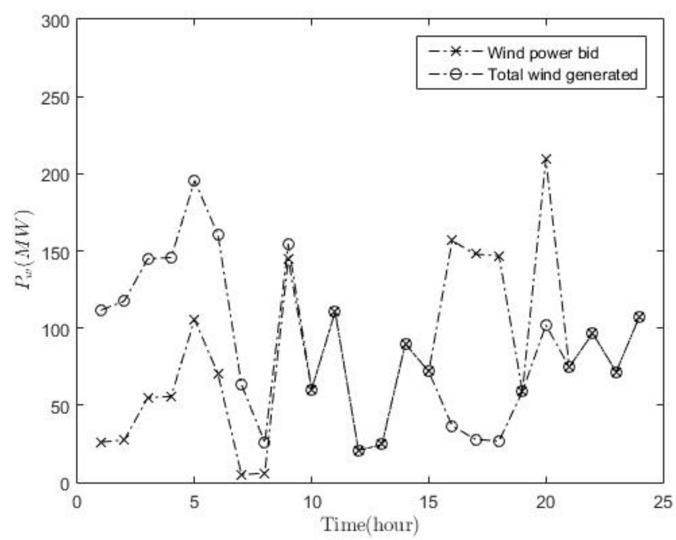

Figure 4.2: Wind farm dispatch in the firs case market using DRO

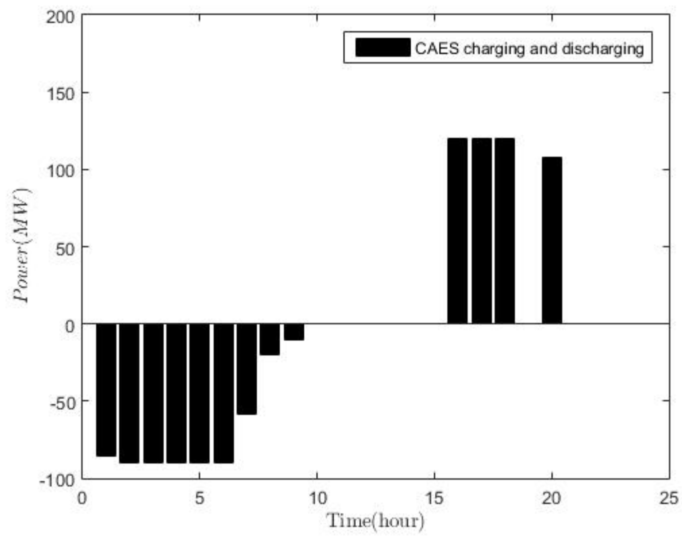

Figure 4.3: Compressing and expanding of the CAES in the first case market using DRO

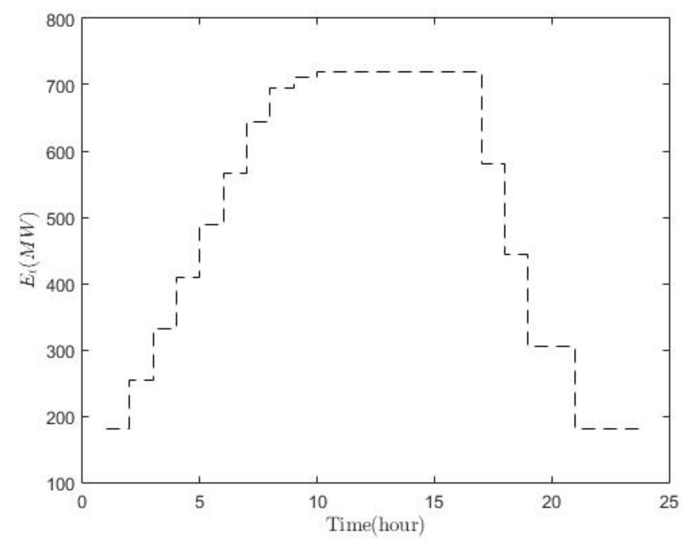

Figure 4.4: Air reservoir level in the first case market using DRO

4.3.3 The optimal bidding scheduling in energy and reserve market using DRO

In this part, the optimal bidding scheduling of the wind farm and CAES participating in energy and reserve market are demonstrated in figure (4.5), (4.6) and (4.7) for the used 24 hours operation horizon. Based on the ambiguity sets of Pg, market prices, and the worst case scenario of the reserve deployment, the combination bidding strategy is submitted. The decision is made to charge the CAES in the off-peak hours and to later dispatch this energy to energy and reserve markets as shown in (4.5), (4.6). In the case when the CAES neither charging nor discharging, the CAES take part to participate in the non-spinning reserve market at hours 9,10, and 24. the dynamic behavior of CAES reservoir is shown in figure (4.7). The expected worst-case profit in this case is \$50176.

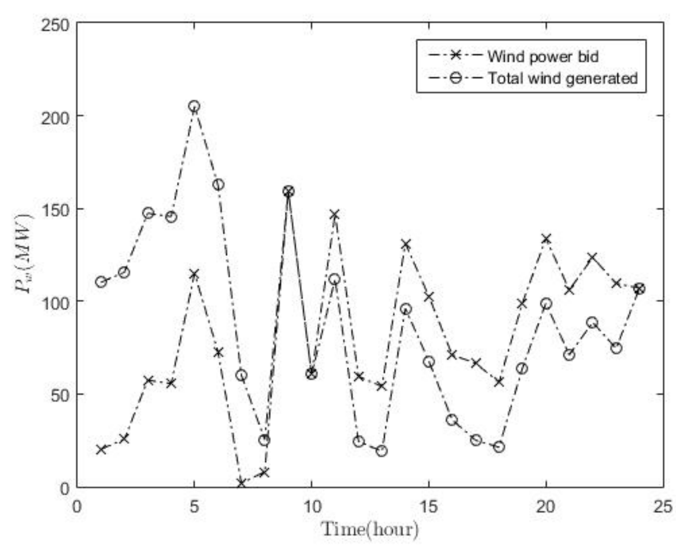

Figure 4.5: Wind farm dispatch in the second considered market using DRO

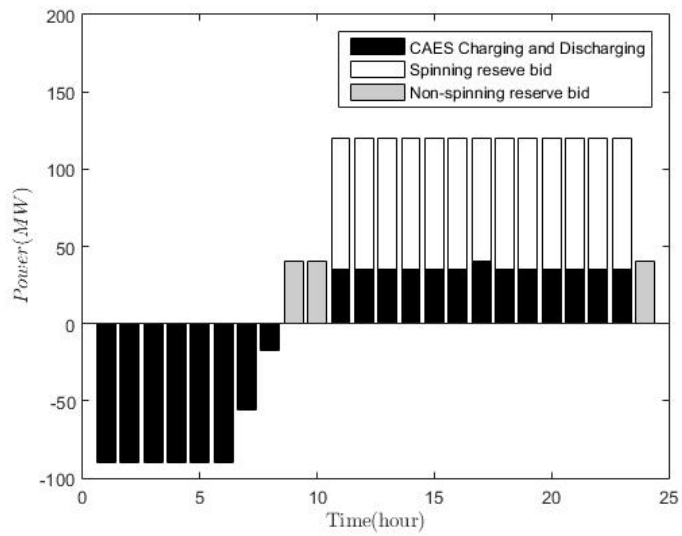

Figure 4.6: Compressing and expanding of the CAES in the second case market using DRO

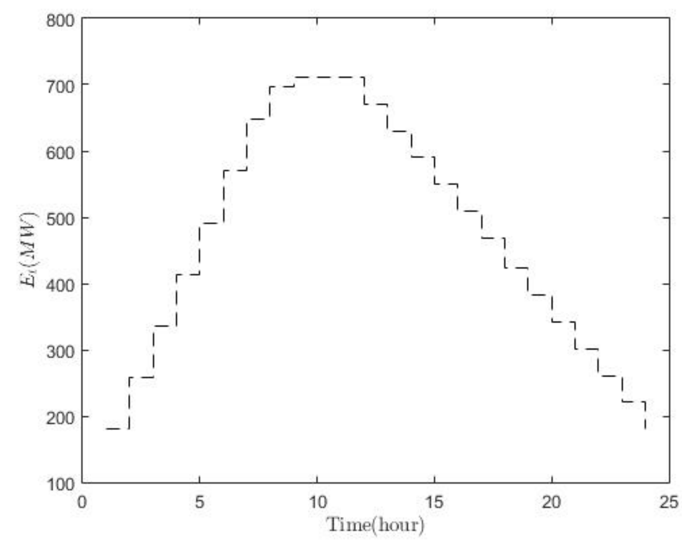

Figure 4.7: Air reservoir level in the second considered market using DRO

4.3.4 The optimal bidding scheduling in energy, reserve, and regulation market using DRO

In this part, the regulation market is added to the DRO optimization problem as seen in figure (4.8), (4.9) and (4.10) to offer a new opportunity to further increase the profit. We can see in figure (4.8) that part of the wind power output used to charge the CAES in the first seven hours. Then, the wind power dispatched using the CAES to participate in energy, reserve and regulation markets as shown in (4.9). The SOC is presented in figure (4.10) which shows that the CAES cannot bid in reserve or regulation markets unless it has enough capacity. The total profit for the 24 hours operation horizon based the DRO optimization is \$53993.

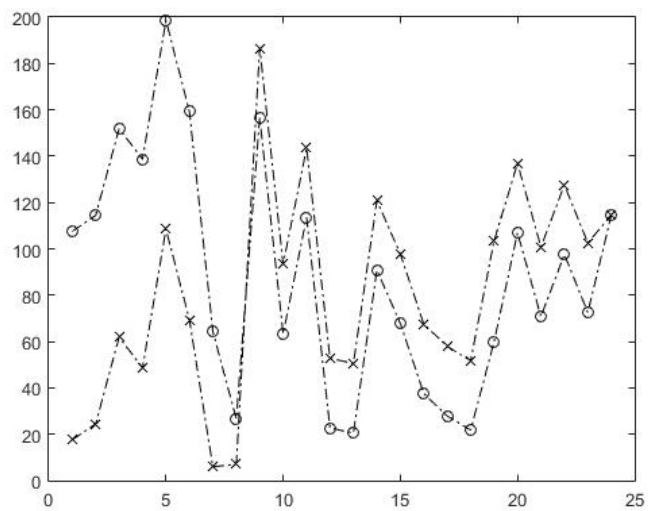

Figure 4.8: Wind farm dispatch in the third case market using DRO

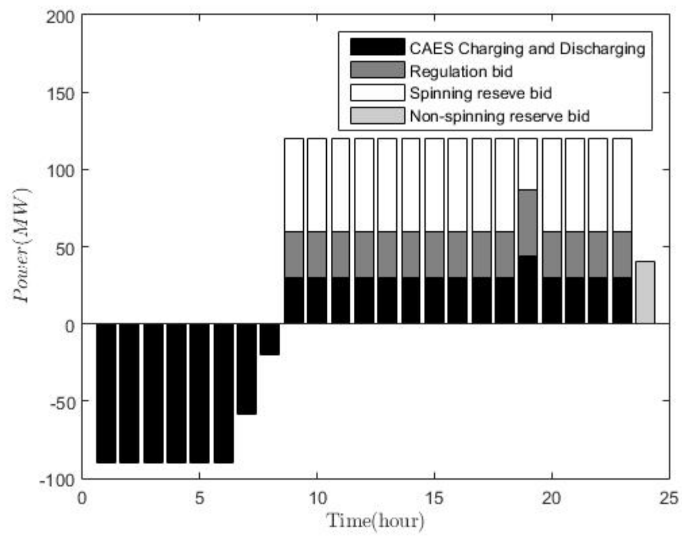

Figure 4.9: Compressing and expanding of the CAES in the third case market using DRO

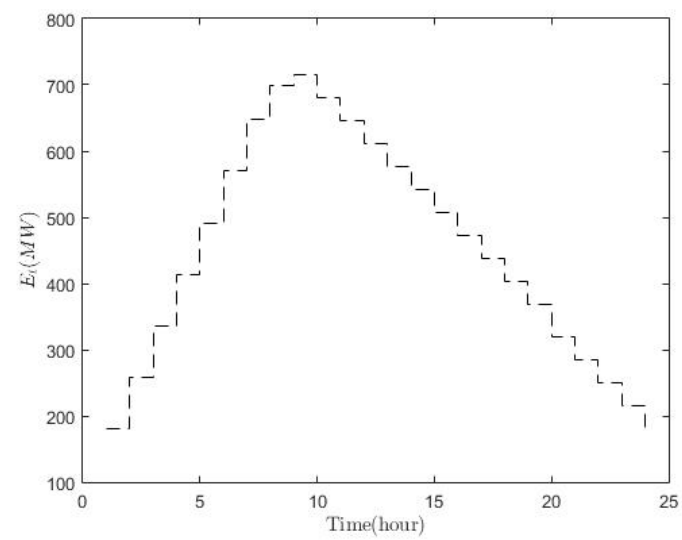

Figure 4.10: Air reservoir level in the third considered market using DRO

4.3.5 Realization for DRO bidding strategy

In this part, a profit comparison of the wind-CAES combination when participating in the three cases considered in this work. Based on the actual wind power

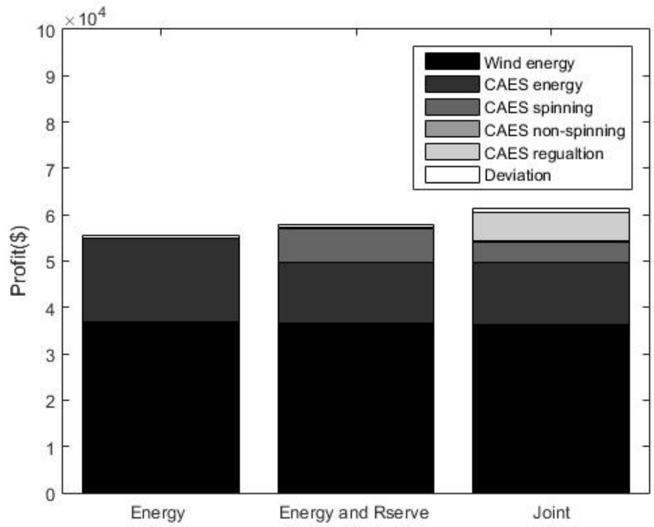

Figure 4.11: DRO profit realization for the three cases

generation, market prices, deployment of reserve and regulation movement the profit is calculated which assumed to be done after the end of the operating day. Since the DRO determine bids based the worst-case expected scenario, almost every hour there is an extra generation power that could be sold in the hour ahead market based on the spot prices. A complete realization for the three cases is shown in figure (4.11). The total profit is gained from participating in the energy market is \$55455. In the second bar, it shows when the Wind-CAES bids in the energy and reserve market, the profit increased to reach \$57761. The third bar is the sum of the profit from energy, reserve, and regulation. Joining the regulation market in the optimization increased the profit to reach \$61354.

4.3.6 The optimal bidding scheduling in energy market alone using robust optimization

The bidding strategy in energy alone market using robust optimization is determined. The robust optimization differs from the DRO in that the profit is calculated based on the worst case scenario and without including any statical data. As shown in (4.12), (4.13), and (4.14), the bidding decision is made based the worst case wind power generated and other uncertain prices. The worst-case profit is \$39881 which is much lower than the expected worst-case profit using the DRO approach.

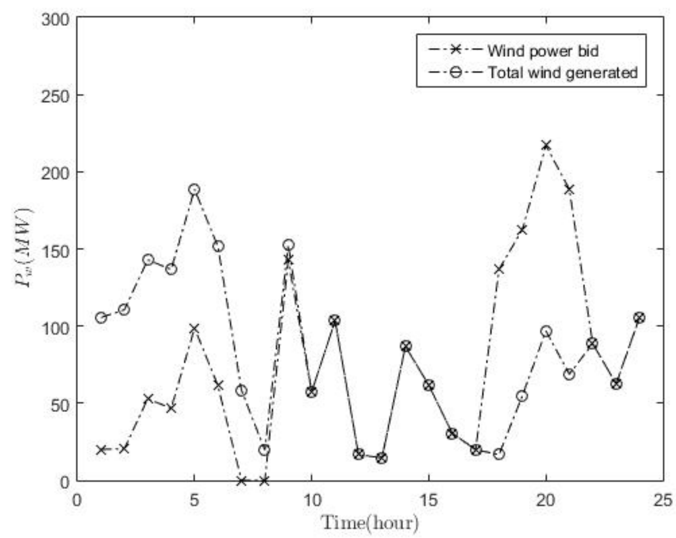

Figure 4.12: Wind farm dispatch in the first case market using robust optimization

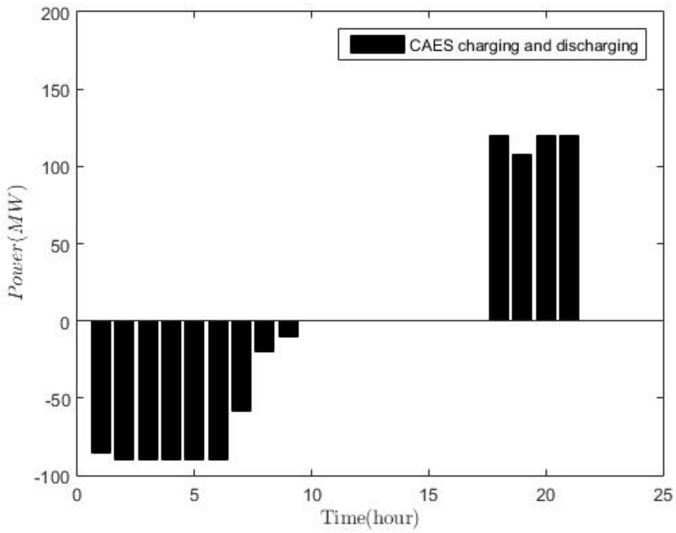

Figure 4.13: Compressing and expanding of the CAES in the first case market

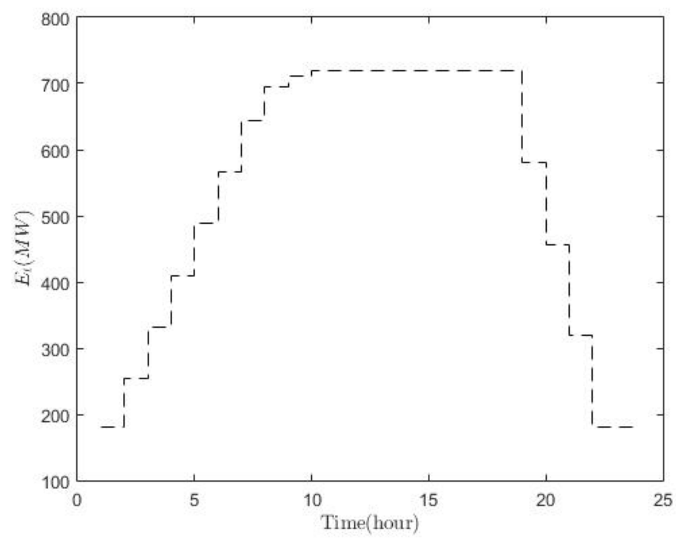

Figure 4.14: Air reservoir level in the first case market using robust optimization

4.3.7 The optimal bidding scheduling in energy and reserve market using robust optimization

The worst case optimal bidding scheduling for energy and reserve market in 24 hours operating horizon is demonstrated in figure (4.15), (4.16) and (4.17).

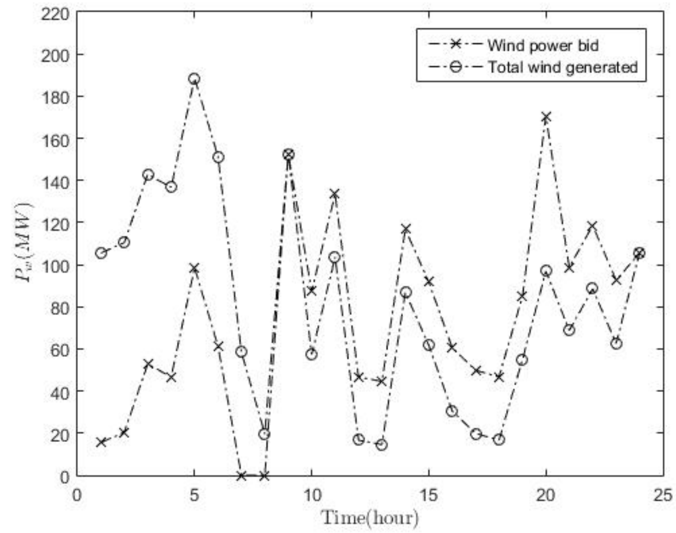

Figure 4.15: Wind farm dispatch in the second case market using robust optimization

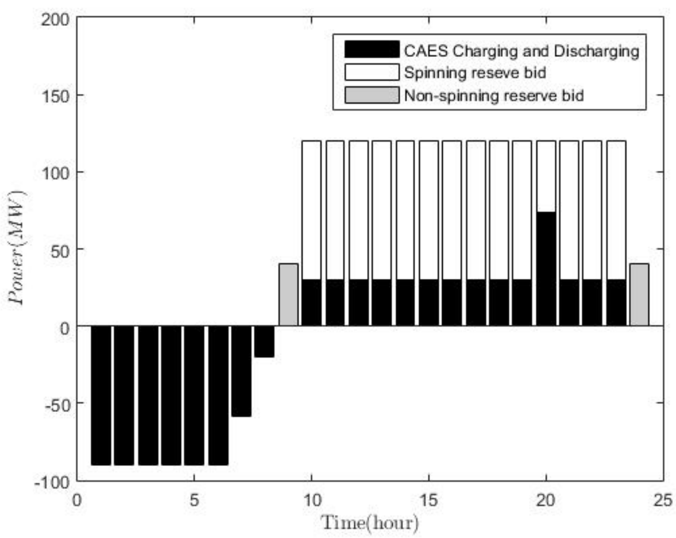

Figure 4.16: Compressing and expanding of the CAES in the second case market using robust optimization

In this part the bidding submitted based on the worst case wind power output, market prices, and reserve deployment which show slit different to the DRO based bidding. Similarly, the decision is made to charge the CAES in the off-peak hours and to later dispatch this energy to energy and reserve markets as shown in (4.15), (4.16). In the idle case the CAES take part to participate in the non-spinning reserve market at hours 9, and 24. the dynamic behavior of CAES reservoir is shown in figure (4.17) and the worst-case profit is \$39881.

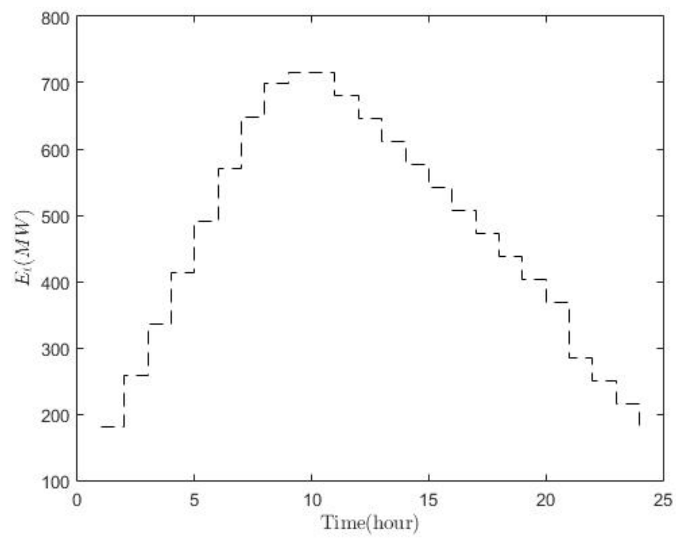

Figure 4.17: Air reservoir level in the second considered market

4.3.8 The optimal bidding scheduling in energy, reserve, and regulation market using robust optimization

The optimal bidding strategy is determined for the Wind-CAES when participating in energy, reserve, and regulation using robust optimization as shown in (4.18), (4.19), and (4.20). As seen in (4.8) similar to DRO based bidding, part of the wind power output used to charge the CAES in the first seven hours. Then, the wind power dispatched using the CAES to participate in energy, reserve and regulation markets as shown in (4.9). However, the bidding is determined using the worst case scenario of wind power output, market prices, reserve deployment,

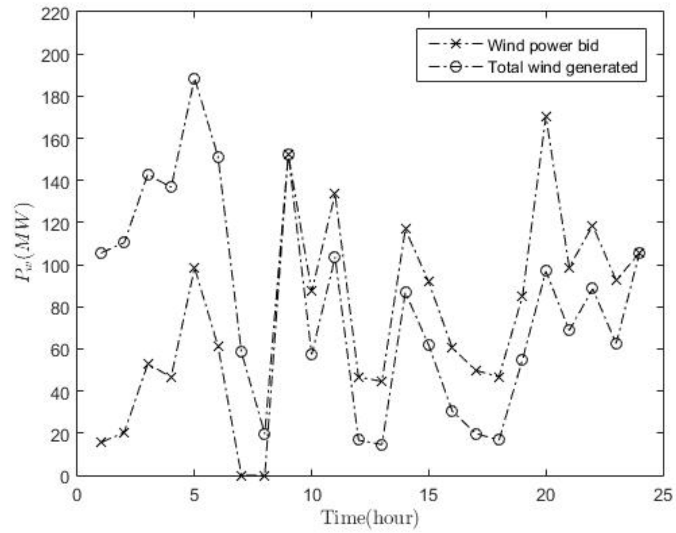

Figure 4.18: Wind farm dispatch in the third case market using robust optimization

and regulation movement. We can notice that in figure (4.19) the CAES regulation bids is reduced dramatically compared to the one in DRO based bidding. The total worst-case profit for the 24 hours operation horizon based the robust optimization is \$40042.

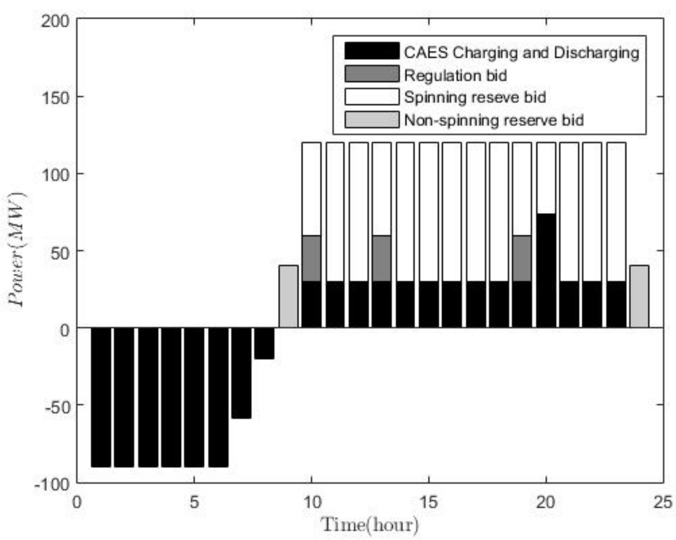

Figure 4.19: Compressing and expanding of the CAES in the third case market using robust optimization

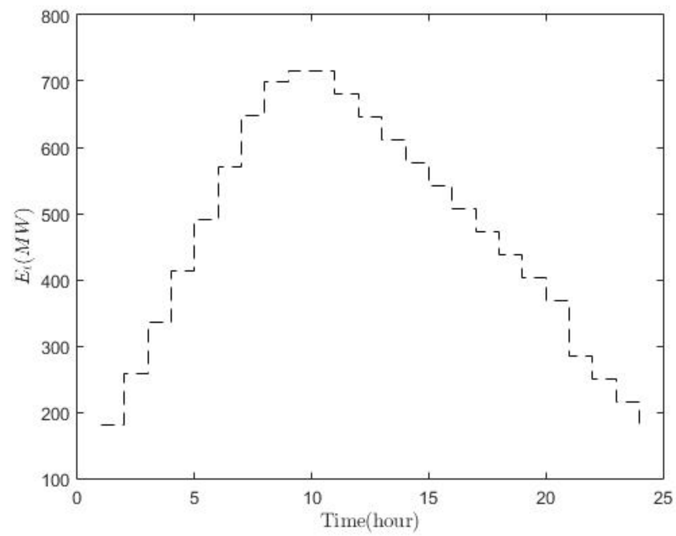

Figure 4.20: Air reservoir level in the third considered market

4.3.9 Realization for robust optimization bidding strategy

A complete realization for the three cases describe the profit from each market is shown in (4.21) . Similar to the realization done for DRO bids based strategy,

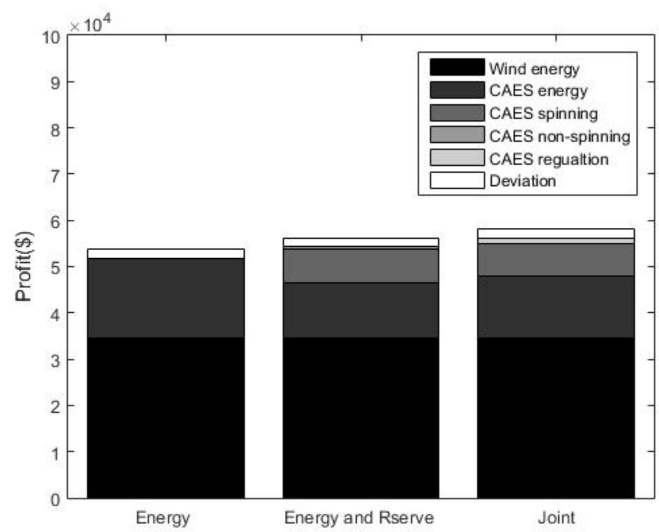

Figure 4.21: robust optimization profit realization for the three cases

the profit is calculated based on the actual wind power generation, market prices, deployment of reserve and regulation movement. Because the scheduled bids determined based the worst-case wind power output scenario, extra actual wind power obtained for each hour which is sold in the hour-ahead market with a penalty based real-time prices. The total profit is gained from participating in the energy market is $53743. In the second bar, it shows when the Wind-CAES bids in the energy and reserve market, the profit increased to reach $56105. The third bar is the sum of the profit from energy, reserve, and regulation. Joining the regulation market in the optimization increased the total profit to reach $58184. the deviation part is the profit from the hour-ahead market which much larger than the one based DRO bids strategy.

4.3.10 Comparison between the bidding stratey based DRO and robust optimization using actual data

In this part, the DRO and robust optimization based bidding scheduling is compared in table (4.1). The expected worst-case profit, realized profit after the operating day, and realization profit as a percentage of the deterministic profit based perfect forecast are calculated for the three cases market using two-stage DRO. Similarly, the worst case profit, realized profit after the operating day, and realized profit as a percentage of the deterministic profit based perfect forecast are calculated for the three cases market using robust optimization. We can notice that the robustness guaranteed for all the cases since the realization always higher than the expected worst-case and worst-case profit. However, incorporating statistical data improve the performance of yielding a better result than the conservative one from the robust optimization. Furthermore, the realization profit as a percentage from the optimal deterministic case for the DRO is always better than robust optimization, and this is because robust optimization bids according to the worst-case wind power generation which result in higher deviations from the actual wind power generations.

Methods		Energy Market ($)	Energy and Reserve Market ($)	Energy, Reserve, and Regulation Market ($)
DRO	Expected WC	46315	49516	53993
	Realization	55455.85	57761.50	61354.57
	% of PFP	91.94%	85.09%	88.19%
RO	WC	37292	39881	40042
	Realization	53743.87	56105.24	58184.82
	% of PFP	89.10%	82.65%	83.64%

Table 4.1: Comparison between DRO and robust optimization based bidding strategy

4.3.11 Comparison between DRO and robust optimization based bidding strategy using Monte Carlo simulation test

An addition profit comparison of the wind-CAES combination when participating in the three cases market using Monte Carlo simulation is applied. The wind farm power output is assumed to follow Gaussian distribution [76]. Similarly, normal distributions are considered for each market prices [77]. Accordingly, 1000 scenarios are generated for wind power generation, market prices, reserve call, and AGC signals to apply the validation test after the bids are submitted. The profits are calculated for all the scenarios, and then the expected profit is presented. The validation test is necessary to see the effectiveness of the bids based DRO comparing to the bids based robust optimization with the scenarios generated from the historical data. Since the DRO and robust optimization used to determine the bids based the worst-case expected and worst-case wind power generation realizations respectively, almost every hour, there is an extra generation power that could be sold in the hour ahead market based on the real-time prices. A complete

Considered Market	DRO	95% CVaR	RO	95% CVaR
First case market ($)	48964.72	3685.23	47126.35	37634.21
Second case market ($)	52142.21	39166.64	50187.63	40355.72
Third case market ($)	54853.35	38768.45	52245.64	40842.46

Table 4.2: Realized profit using DRO and robust optimization

validation test comparison for the three cases market is shown in table (4.3.11). The total expected profits gained from participating in the energy market for the bids using DRO and robust optimization are $48264 and $47326. In the second line when the Wind-CAES bids in the energy and reserve market, the expected profit for the DRO and robust optimization bids are $51742 and $49612. Lastly, the realized expected profit from energy, reserve, and regulation markets. Joining the regulation market in the DRO optimization added extra $2511 expected profit to reach $54253, and extra $2633 expected profit to reach $52245 using robust optimization. The third and fifth columns indicate the expected shortfall to measure and quantify the tail risk associated with the 10% of the whole scenarios.

4.3.12 The effect of the CAES capacity on the worst-case expected profit

In this part, different CAES capacities are introduced to the case study. The purpose is to evaluate the influence of the CAES size on the hedging assigned to the wind farm used in this work. The worst-case expected profit is determined for each of the CAES sizes starting with 240 to 3600 MWh. Accordingly, modifications carried out to the compression, expansion, and QSC with an equivalent rate of the CAES air reservoirs. The worst-case expected profits for each of the considered CAES capacities are shown in figure (4.22). An increase of the obtained profits for

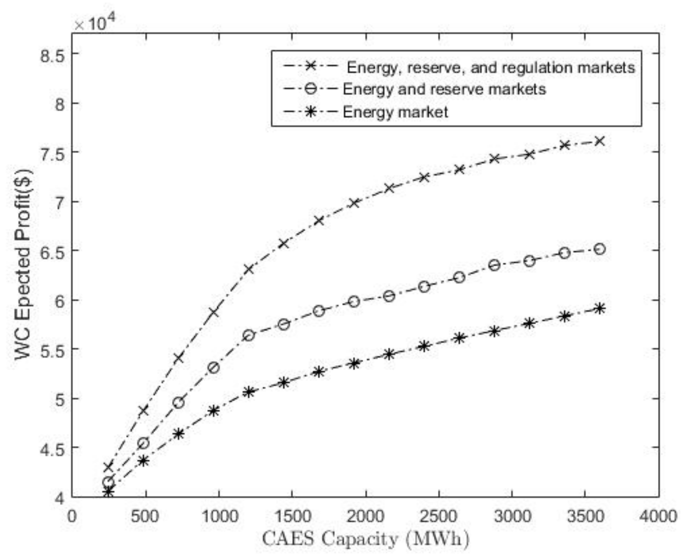

Figure 4.22: The influence of the CAES size on the profit

all the three cases markets with a relatively higher increase rate for participation in the third case market is presented. It is reasonable because in the third case market there are multiple markets which give more options to CAES bids. Furthermore, one can notice that when the CAES compression reaches the size of the wind farm, the profits increase at a slower rate for the three cases.

CHAPTER 5

CONCLUSION AND RECOMMENDATION FOR FUTURE WORK

5.1 Conclustion

The coordinated participation of wind farm and compressed air energy storage system in deregulated electricity market using distributionally robust optimization have been discussed in this thesis. In the first part, the mathematical model formulation for the combination of wind farm and CAES participating in New York energy and ancillary services markets were studied. The ancillary services market includes spinning-reserve, nonspinning-reserve, and regulation was considered in the model. For spinning-reserve and nonspinning-reserve market, the capacity scheme was applied while the pay for performance mechanism was used for regulation deployment. Numerical simulations were represented to test the performance and effectiveness of the deterministic proposed model.

In the second part, a reformulation for the deterministic objective function using two-stage DRO was included. This approach was used to address the uncertainty associated with wind farm power output, market prices, reserve deployment, and regulation movement. For the reserve deployment and regulation movement, the worst case scenario is considered, while the other uncertain parameters were described using ambiguity sets. Accordingly, the optimal bids scheduling strategy was obtained for the three cases.

A comparison was made in the last part with the robust optimization for the three cases. The DRO based bidding strategy has less conservative results than the robust optimization. Furthermore, the realization profits for DRO bidding was higher than robust optimization for all the three cases, and this is because of the incorporating of statistical data. Additionally, a validation test was included using Monte Carlo simulation for 1000 scenarios to show the effectiveness of the proposed approach. Analysis of the CAES size also was studied at the end of chapter 4.

5.2 Recommendation for Future Work

The limitations of the proposed work indicate the following directions to be investigated.

1. To add possible solar farms to the combination. In some areas, the variability

of wind and that of solar are complementary and would increase the value of a CAES and better justify the investment cost.

2. To develop the proposed model by considering the system as a price maker. Since the work in this thesis assumed there is no effect of the system on the grid, expand the system as a price maker will be an excellent direction to be investigated.

3. To study the possibility of expanding the proposed formulation to include distributed energy resources. e.g., distributed battery or electric vehicle participating in a vehicle to grid (V2G) service that is meant to mitigate wind plant bidding risk.

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Vitae

Personal Details

Name	Mohsen Hassan Aldaadi
Nationality:	Saudi
Date of Birth	October 14, 1989
Email:	eng.maldaadi@gmail.com
Permenant Address:	7996 unit No. 6, Waly Al Ahd, Makkah, SA
Phone:	+966562134001

Education

2007-2012	B.Sc Electrical Engineering Umm Al-Qura University, Makkah, Saudi Arabia
2015-present	M.Sc Electrical Engineering King Fahd University of Petroleum and Minerals, Saudi Arabia.